New Loan Acquisitions Model

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Whitepaper

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Version Log

Version No.	Date	Changes	Author(s)
1	May 4, 2015	First draft	Rob Gilbreath
2	Oct 29, 2015	Fill in Theoretical Background, Limitation, Conclusion, reference sections. Update PMM HP and IR sensitivity charts	Ning Ma
3	Sep 27, 2016	Add flowchart, dependent variable definition, t-value statistics, PTC chart, estimation period	Ning Ma
4	Oct 4, 2016	Move Refi Loan Size section into Assumptions	Ning Ma

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Executive Summary

The New Loan Acquisition Model forecasts the monthly acquisition of new loans in Fannie Mae's mortgage portfolio for up to 60 months. The model projects monthly acquisition loan counts, decomposed into purchase, rate/term refinance, and cashout refinance acquisition types, and these are further decomposed into ARM, FRM15, and FRM30 products. The primary drivers of acquisition volume and profile are home price paths, interest rates, and forecasted prepayment activity. The model has been in use in the Loss Forecast Model (LFM), and this update will allow it to be used in the Common Cash Flow Application (CCFA) as well.

The LFM is a system of econometric regressions sequentially estimating various payment-related metrics over the lifecycle of a loan on Fannie Mae's single-family portfolio: acquisition volume, delinquency probability, liquidation probability and loss severity. The transition models consist of a suite of prepayment, repurchase, delinquency, default, and modification models to estimate the probability of an event occurring next month, conditional on loan activity in the current month.

CCFA is a system designed to produce loan level cash flow projections and calculate guarantee fees commonly used for a variety of major business applications on Fannie Mae's Single Family book of business. The CCFA model suite consists of incidence models, providing the probabilities of events like delinquency, default, prepayment, etc., and severity models, providing cash flows for default outcome.

Introduction

The key objectives of this model update are:
1. Ensure that the same model can be used in both LFM and CCFA
2. Bring the purchase forecast into closer alignment with ESR purchase forecasts
3. Improve the model's responsiveness to economic conditions (namely changes in home price and interest rates) and improve performance under stress scenarios.
4. Simplify the models, reducing explanatory variables by using clearly defined economic drivers rather than statistical drivers
5. Refresh the data to include more recent data and align with CCFA and LFM data

The overall structure is largely the same: First purchase acquisition count is forecasted, then total refinance count using forecasted prepayment activity. Refinance is then decomposed into rate/term and cashout refinance types, and then product shares are modeled for each acquisition type. The two significant structural changes in this update are:
1. A first time borrower model is introduced and used as part of the calculation of refinance count
2. The cashout refi ARM share model and rate/term refi ARM share model are consolidated into a single refi ARM share model.
3. The cashout refi FRM15 share model and rate/term refi FRM15 model are consolidated into a single refi FRM15 share model.

The New Loan Acquisition Model has 15 components:

1. Purchase loan count
2. Purchase loan UPB
3. Cashout refi ratio
4. Cashout rate incentive
5. Purchase ARM ratio
6. Purchase FRM15 ratio
7. Refi ARM ratio
8. Refi FRM15 ratio
9. Cashout Refi UPB assumption
10. Rate-term Refi UPB assumption
11. Cashout Refi LTV assumption
12. Rate-term Refi LTV assumption
13. First time home borrower ratio assumption
14. Prepay replenish rate assumption
15. Purchase loan count intercept adjustment assumption

The output for each component is explained in the section “Model Outputs” and each is treated individually in the section “Final Model Structure”. The key drivers for each model are described, along with the specification, estimation method, and coefficients where applicable.

Model Uses / Purpose

The New Loan Acquisition Model will be used in the LFM and in CCFA to allow those systems to produce forecasted performance of future acquisitions.

Business Uses

The New Loan Acquisition Model extends the LFM and CCFA systems to forecasting activity for future acquisitions. The usage of this capability includes, but is not limited to, business planning, corporate expense forecasting, revenue forecasts, and portfolio size management.

Model Dependencies

The model has a number of upstream dependencies: National home price history and forecast, interest rate history and forecast, state-level median household income history and forecast, and a forecast of monthly Fannie Mae market share. It also depends on a monthly prepayment forecast which can either be provided as an input or by LFM/CCFA during execution.

Model Scope / Applicability

The scope of the New Loan Acquisition Model is the same as LFM and CCFA, which cover all loans excluding government, seconds, and reverse mortgages.

Model Outputs

Definition

The New Loan Acquisition Model outputs values for the following variables. For each variable there is one value output for each month of the forecast period:

- Purchase loan count
  - Total count of purchase loans acquired into the Fannie book
- First time borrower count
  - Total count of purchase loans that belong to first time borrowers
- Refi count
  - Total count of refinance loans acquired into the Fannie book
- Cashout refi ratio
  - Cashout loan count as a ratio to the total refi acquisitions
  - (cashout loan count) / (cashout loan count + rate/term loan count)
- Purchase ARM ratio
  - Purchase ARM count as a ratio to the total purchase acquisitions
  - (ARM count) / (ARM count + FRM15 count + FRM30 count)
- Purchase FRM15 ratio
  - Purchase FRM15 count as a ratio to the total FRM purchase acquisitions

    - (FRM15 count) / (FRM15 count + FRM30 count)
- Refi ARM ratio
    - Refi ARM count as a ratio to the total Refi acquisitions
    - (ARM count) / (ARM count + FRM15 count + FRM30 count)
    - The same ratio is used for cashout refi and rate/term refi
- Refi FRM15 ratio
    - Refi FRM15 count as a ratio to the total FRM Refi acquisitions
    - (FRM15 count) / (FRM15 count + FRM30 count)
    - The same ratio is used for cashout refi and rate/term refi

Theoretical Background

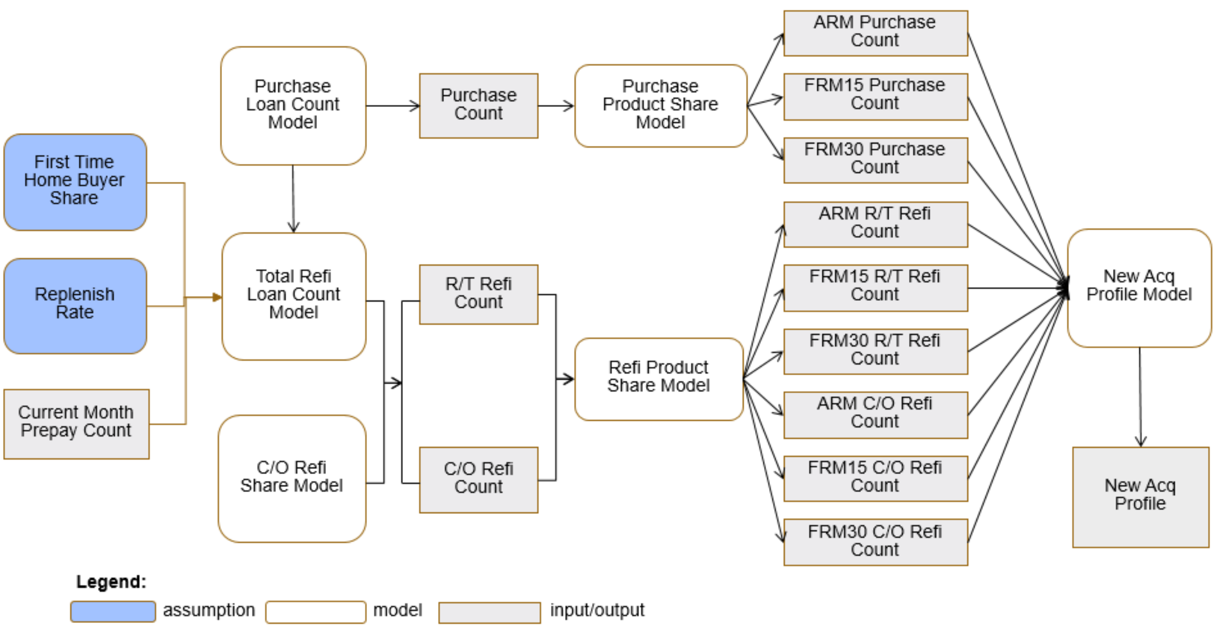
Single-family mortgage originations are the sum of purchase and refinance originations. LFM divides the forecasting of these into two separate models. For purchase originations, a linear regression is used to estimate PMM count in logarithm term. Model specification only includes home price, interest rate, FNMA share and seasonality related variables, to capture economic environment in the most efficient way. For refinance originations, a simple formula derives origination amount from concurrent prepay and purchase, such that it equals FNMA acquired prepay minus non-turnover purchase.

Alternative Structures / Methodologies

The existing new loan acquisitions model has a similar structure to the updated model, but each component model is an autoregressive moving average (ARMA) model. The moving average part of each model is dependent on interest rates, home prices, and seasonality. The autoregressive part is dependent on lagged error values of the model output. Such a model structure is lack of transparent connection between economic environment and forecasted activity, and more like data mining.

Final Model Structure

The New Loan Acquisition Model is part of the main loop of the LFM that forecasts the transitions of loans in Fannie Mae's mortgage portfolio on a monthly basis. Each month, the loans in the portfolio may prepay, default, or change delinquency status, and the borrower may cancel mortgage insurance. Loans are also added to the base population each month due to new acquisitions of loans. This final step – the forecast of monthly loan acquisitions – is the responsibility of the New Loan Acquisition Model. The flowchart depicts the structure of the Acquisition Model, which projects the future business volume of nine sub books. Home Purchase Model and Refi-Ratio Model together determine the total volume of home purchase and refinance acquisitions. The Cashout Ratio Model forecasts the percentage of refinance volume that belongs to cashout, and hence divides the total acquisition into three pools. Finally, the Product Share Model further divides each pool into FRM30, FRM15, and ARM, producing the forecast of nine sub book volumes.



Purchase Loan Count

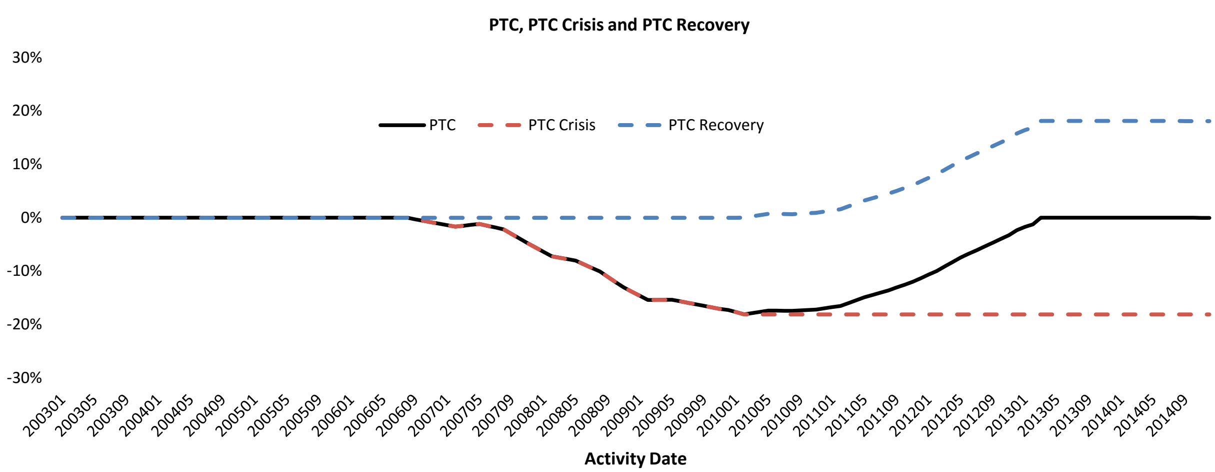
Key Drivers

We want the purchase loan count forecast to be driven as much as possible by home price and interest rate changes so the forecasts will respond to different economic scenarios. Therefore we use home price growth and interest rate growth as explanatory variables, and limit the addition of other independent variables as much as possible.

We use the following drivers to determine purchase loan count:

- HP peak-to-current crisis
- HP peak-to-current recovery
- FRM30 affordability index (assuming 28% DTI)
- Fannie market share: While total market purchase count is driven largely by home prices and interest rates, Fannie purchase count is also affected by Fannie market share. Because market share is largely policy driven, we propose that this be a user-configurable input to the model.
- Seasonality: The historical data shows clear seasonality trends. Therefore we add calendar month dummy variables to capture rises and falls in purchase activity over the course of the year.

To be aligned with CCFA Prepay model HPI variables, we use the past 3 years' national HPI behaviors to measure macro economic conditions. This variable is HP peak-to-current growth, or the HP growth rate from the highest HP level in the last 3 years to the current activity date. It is always non-positive. One problem with the PTC variable is that it is pretty symmetric with the passage of time as figure below shows. But since fear is often a much stronger motivator than greed, we should expect people's purchase event is more responsive to market downturns than market recovery. In order to better capture the asymmetric nature of market response to such event, we break down total PTC into PTC crisis and PTC recovery, and allow their parameters to be estimated separately. These PTC variables are shown below, and PTC crisis parameter is more than 3 times of PTC recovery.



Purchase Loan Count Model

The purchase model is a linear regression with ln(purchase count) as the dependent variable.

Variable	Coefficient	t-Value	Prob>|t|	Interpretation
Intercept	12.65147	108.6	<.0001	
pmm_hp3yr_ptc_us1	6.932429	30.63	<.0001	3 year peak-to-current HP growth, assuming no recovery post crisis
pmm_hp3yr_ptc_recov_us	2.054711	8.92	<.0001	3 year peak-to-current HP growth recovery
pmm_affordability_index_f30	0.068303	0.83	0.4071	FRM30 affordability index
pmm_md_ttl_1	-0.30978	-10.33	<.0001	Seasonal Dummy for January
pmm_md_ttl_2	-0.25341	-8.6	<.0001	Seasonal Dummy for February
pmm_md_ttl_3	-0.11348	-3.8	0.0002	Seasonal Dummy for March
pmm_md_ttl_4	-0.04343	-1.44	0.1516	Seasonal Dummy for April
pmm_md_ttl_5	0.067552	2.27	0.0247	Seasonal Dummy for May
pmm_md_ttl_6	0.211173	7.16	<.0001	Seasonal Dummy for June
pmm_md_ttl_7	0.137331	4.54	<.0001	Seasonal Dummy for July
pmm_md_ttl_8	0.145802	4.82	<.0001	Seasonal Dummy for August
pmm_md_ttl_9	0.123907	3.95	0.0001	Seasonal Dummy for September
pmm_md_ttl_10	0.050819	1.68	0.0958	Seasonal Dummy for October
pmm_md_ttl_11	-0.01648	-0.54	0.5874	Seasonal Dummy for November
pmm_share_ttl	0.516137	14.06	<.0001	Fannie market share

Cashout refi ratio

Key Drivers

The share of refi loans that are cashout refis is driven by two key economic factors:

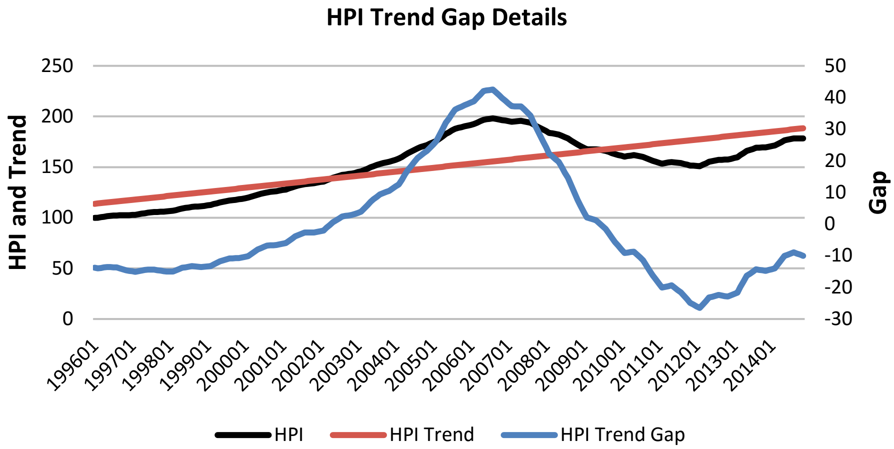
- Rate incentive: When rates decrease, more borrowers will refinance to take advantage of the better rates, and cashout refis will represent a smaller share of total refis. Conversely, when rates increase, more refis will be the result of cashouts.

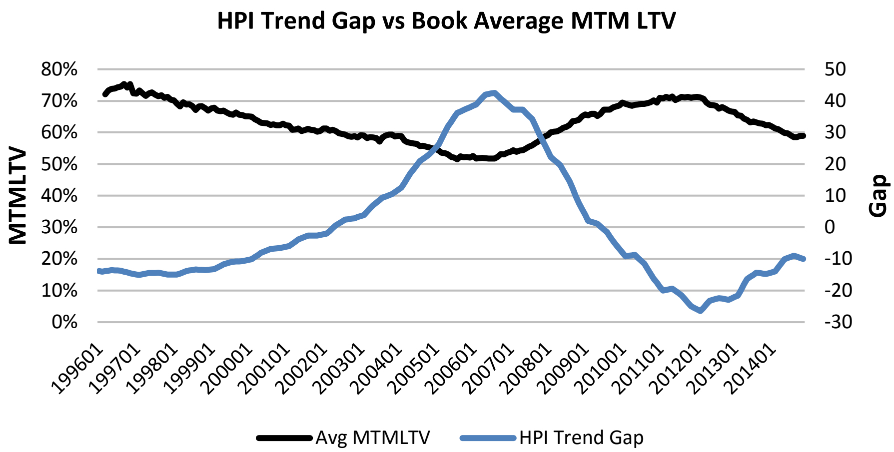
- MTM LTV: Cashout refis also require a certain amount of equity (usually 20-25%[1]). When, on average, loans have high MTM LTV, we expect cashout refis to represent a smaller share of total refis, and when loans have low MTM LTV, more refis will be cashout refis.

Calculating average MTM LTV for the entire book for each month of the forecast is not computationally feasible. Instead, we use the difference between HPI and the “expected” HPI from the linear HPI trend of the course of the estimation period. When HPI is significantly higher than the trend, we expect loans to have low MTM LTV because home prices are growing rapidly.

[1] Source: http://www.freddiemac.com/singlefamily/guide/ Single-Family Seller/Servicer Guide Section 23.4 Maximum LTV, TLTV and HTLTV ratios

Conversely, when HPI is lower than the trend would say, MTM LTV will high. This is observed in the data:





Cashout Ratio Model

The cashout refi ratio model is a two-stage model: first stage estimates average rate incentive at the national level, and second stage estimates cashout ratio using first stage output as input variable. Rate incentive is defined as current note rate minus market rate.

The rate incentive model is a linear regression using FRM30 growth in the previous five years, where dependent variable is average rate incentive.

Variable	Coefficient	t-Value	Prob>|t|	Interpretation
Intercept	4.46657	19.54	<.0001	
frm30_1yrgr	-0.5154	-1.9	0.0595	1 year ago FRM30 Growth
frm30_2yrgr	-1.02856	-3.23	0.0015	2 year ago FRM30 Growth

frm30_3yrgr	-1.9858	-5.86	<.0001	3 year ago FRM30 Growth
frm30_45_avg	-0.9594	-3.13	0.0021	Avg of 4 and 5 year ago FRM30 Growth

The cashout ratio model is also a logistic regression, using rate incentive and HPI trend gap. The model, then, uses the primary observable economic drivers (rate incentive and MTM LTV), ensuring that it changes logically under different economic scenarios. Second stage model dependent variable is ln(Cashout Share/(1-Cashout Share)), to guarantee predicted value never go beyond 0-1 boundary.

Variable	Coefficient	t-Value	Prob>|t|	Interpretation
Intercept	-0.2305	-8.8	<.0001	
rate_incentive	-0.35356	-9.24	<.0001	modeled rate incentive
hpi_trend_gap	2.73678	28.75	<.0001	Difference between HPI and long-term HPI linear trend

Purchase ARM share and refi ARM share

Key Drivers

The choice of an ARM product over an FRM product has three key economic drivers:

- Affordability: ARM payments start out smaller than FRM payments because they have lower interest rates at origination. When the monthly payment of an 80 ltv loan at the current home price and FRM30 interest rate levels exceeds 28% of income, we would expect more people to choose ARM products, and vice versa.

- FRM30 ARM spread: The larger the difference between FRM30 rates and ARM rates, the more enticing an ARM product will be.

- HP growth: If home prices are growing significantly, more borrowers will choose ARM products, expecting to have low MTM LTV when their rate resets and having the option to sell or refinance.

We use an affordability index, defined as the ratio of affordable home price (the total loan amount that would require a payment equal to 28% of the US median home monthly income at the current FRM30 rate and a 360 month term) to the current median home price. A value greater than 1 means FRM loans are very affordable and a value less than 1 means FRM loans are not affordable.

We use ARM 5/1 rates to define the FRM30 ARM spread because ARM 5/1 loans are the most common ARM products in Fannie's historical book.

To identify periods of strong growth, we use the hp3yr_ttc variable used in CCFA, defined as the HP growth rate from the lowest level in the last 3 years to the current activity date.

Purchase ARM share and refi ARM share models

The purchase ARM ratio and refi ARM ratio models are logistic regressions using the same specifications, but have different coefficients. Dependent variable is ln(ARM Share/(1-ARM Share)), to guarantee predicted value never go beyond 0-1 boundary.

	Refi			Purchase			
Variable	Coefficient	t-Value	Prob>|t|	Coefficient	t-Value	Prob>|t|	Interpretation
Intercept	-1.16198	-2.59	0.0102	-1.24932	-3.33	0.001	
affordability_index_f30	-2.01431	-6.13	<.0001	-1.68343	-6.13	<.0001	
arm51_frm30_spread100	0.82274	5.28	<.0001	0.56593	4.32	<.0001	spread between ARM 5/1 and FRM 30 rates
hp3yr_ttc_us_pre_rec_cap1	4.45052	4.63	<.0001	5.51879	6.86	<.0001	maximum hp growth in last 3 years, capped at 0.1 and set to zero post recession

The purchase FRM15 ratio and refi FRM15 ratio models are logistic regressions using the same specifications, but have different coefficients. Dependent variable is ln(FRM15 Share/(1-FRM15 Share)), to guarantee predicted value never go beyond 0-1 boundary.

Purchase FRM15 share and refi FRM15 share

	Refi			Purchase			
Variable	Coefficient	t-Value	Prob>|t|	Coefficient	t-Value	Prob>|t|	Interpretation
Intercept	-3.53036	-24.25	<.0001	-4.07079	-31.16	<.0001	Constant
affordability_index_f30	-3.70458	-11.48	<.0001	-2.35788	-8.16	<.0001	Ratio between "affordable" home price (assuming FRM30, 28% DTI, and 80% LTV) and median home price

affordability_ index_f15	7.22601	13.68	<.0001	4.80827	10.16	<.0001	Ratio between "affordable" home price (assuming FRM15, 28% DTI, and 80% LTV) and median home price
frm15_frm30 _spread100	1.42188	12.12	<.0001	0.58323	5.5	<.0001	spread between FRM 15 and FRM 30 rates

Loan Size and LTV Update

Purchase loans in the future are expected to have different loan sizes due to changes in the payments borrowers are able to afford (determined by income and interest rates) along with the changes in home prices market-wide. Refi loans in the future are expected to have loan sizes and LTVs reflecting the concurrent prepayment population, as determined by the incidence models.

Purchase loans

We model nation-wide front end DTI with a linear regression on FRM30yr affordability index:

Variable	Coefficient	t-Value	Prob>|t|	Interpretation
Intercept	0.353267	39.81	<.0001	
affordability_index_f30	-0.06392	-10.12	<.0001	Ratio between "affordable" home price (assuming FRM30, 28% DTI, and 80% LTV) and Median home price

This allows us to define activity date dti at time t in terms of book date dti, book date affordability index, and affordability index at time t:

```
activity_date_dti = book_date_dti + ( -0.06392 ) * ( affordability_index_f30 – book_date_affordability_index_f30 )
```

Given US income at time t we can define the target mean origination amount for purchase loans as:

```
activity_date_pmt = activity_date_dti * ( US income / 12 )

activity_date_orig_amt = mort( . , activity_date_pmt , frm30yr / 12 , 360 )
```

The origination amounts for purchase acquisitions are then adjusted to achieve the target population mean.

Estimation Data

The development dataset used to construct the New Acquisition Model includes monthly observations from 2001 to 2014. The details of data construction are as follows.

Data Sources

The estimation data is created using the following data sources:

- v_ln_static_data_est: static loan level oracle view created and maintained by the data prep team for CCFA and LFM estimation
- ll_ln_appl: RDW table with first-time borrower data
- Market rate inputs: historic monthly market rates for 15 and 30 year FRM loans are the two month lagged "zero point" Freddie PMMS survey rate. These are available in the IRDB. We extracted our data from VN's standard market (PMMS_AVG for FRM30 and PMMS_AVG_15 for FRM15) which also source its data from IRDB. For ARM products, we used the following expression
  $$market\_rate(t) = PMMS15(t-2) + prod\_spread + \beta(libor10(t-2) - libor1(t-2))$$
  for the market rates. Here the parameters prod_spread and are determined from a regression with the LHS being the average origination rates for each product, such as ARM11, ARM31 and etc. The historic 1 and 10 years LIBOR rates used in the above regression were also extracted from CMS1 and CMS10 series from VN's standard market, respectively.
- US HPI: usinx14m12_wgt_cnty
- household_income.csv: LFM production parameter file created from DataBuffet data

Dataset Construction

Dependent variables are created by taking total acquisition counts by purpose (purchase, cashout refi, rate/term refi) and product (ARM, FRM15, FRM30) for each month during the estimation period. All dependent variables (Purchase loan count, first time borrower count, refi count, cashout refi ratio, purchase ARM ratio, Purchase FRM15 ratio, refi ARM ratio, refi FRM15 ratio) are defined in terms of these totals.

Data Validation

Because this is aggregated data, we do not need to apply any filtering, data correction, or sampling logic. Explanation of the treatment of missing values, outliers, censored or truncated data doesn't apply.

Assumptions (Dials)

Model Inputs

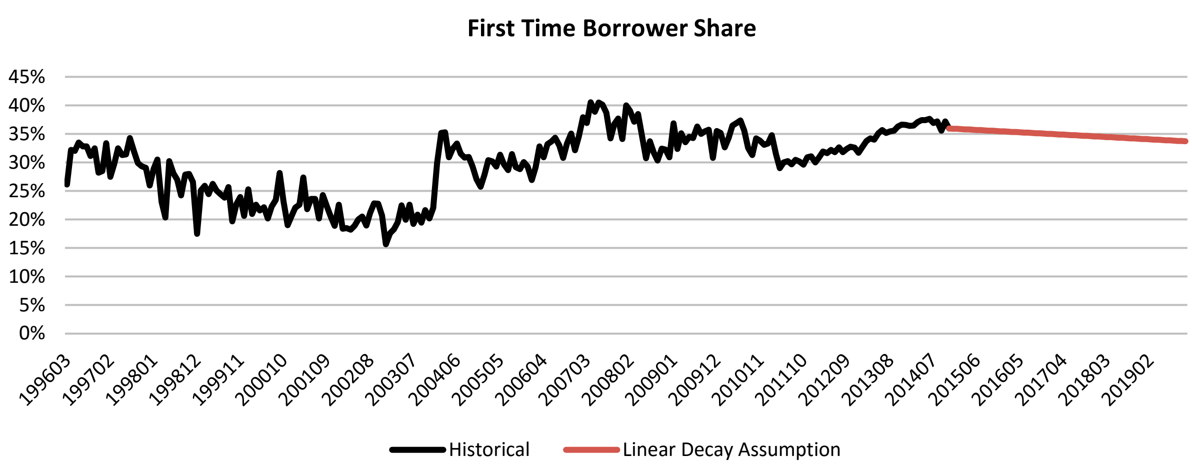
The new loan acquisitions model uses four key inputs that are used to define refi count: purchase count intercept adjustment, first time borrower share, replenishment rate, refi loan size.

Purchase Count Intercept adjustment

Purchase count intercept adjustment is currently 0, but the value will be a configurable parameter that users can change, in order to change projection.

First Time Borrower Share

First time borrower volume as a share of total purchase volume has a number of drivers that we do not have a means of forecasting, including unemployment and new home construction. We make a simple assumption that the most recent month's first time borrower share will converge with the average monthly share from the 2005-2014 period over 60 months. The duration of the decay from short- to long-term First Time Borrower share is also configurable in implementation, and there is also an option for users to specify a customized time series of First Time Borrower count



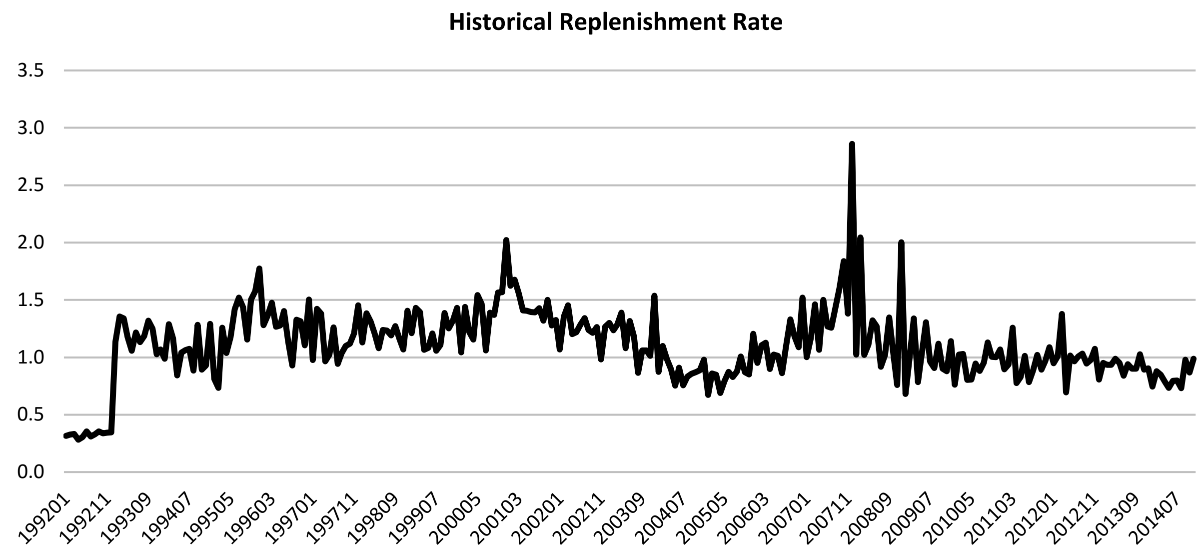
Replenishment Rate

The number of refi loans acquired by Fannie should be driven by prepayment. In an idealized closed system, all prepayments would return to the portfolio as refis. However, prepayments from Fannie can be acquired by other institutions, and refis acquired by Fannie can come from prepayments in other institutions' portfolios. We define a "replenishment rate" ratio γ as:

$$\gamma = \frac{(\text{Purchase} + \text{Refi}) - \text{First Time Borrower}}{\text{Current Month Prepay}}$$

Where “First time borrower” is a proxy for non-turnover volume (we cannot directly identify non-turnover in our data, but can identify first time borrowers).

When γ = 1 – (first time borrower / prepay), acquisitions fully compensate for prepayments. When γ is larger, the profile adding more loans than it is losing to prepayment, and when γ is smaller, the profile is not adding as many loans it is losing to prepayment. Whether the forecasted profile size grows or shrinks is, then, a function of γ, forecasted first-time borrower count, forecasted prepayment count, forecasted default count, and forecasted repurchase count. The value of γ will be a configurable parameter that will give users control over the forecasted portfolio growth. Historically, the replenishment rate is close to 1:



Given γ, purchase and first time borrower count from the models and assumptions described in this paper, and prepayment from either the LFM or CCFA, refi count can be defined as

$$\text{Refi} = \gamma \cdot \text{Current Month Prepay} - \text{Purchase} + \text{First Time Borrower}$$

Refi Loan Size

The size and LTV of refi acquisition loans is expected to be connected to concurrent prepayments. Historically we compare the UPB and LTV of refi acquisitions to those of prepayments less than 10 years old and with amortization terms of 30 years or more, and see the following ratios:

Cashout Refi / Prepay LTV: 0.9727089

Rate/Term Refi / Prepay LTV: 1.0467178

Cashout Refi / Prepay UPB: 1.0133184

Rate/Term Refi / Prepay UPB: 1.0834942

Given the prepay population average UPB and LTV, we use these ratios to produce target UPB and LTV for the acquisition cashout and rate/term refi populations, and adjust the acquisition loans accordingly.

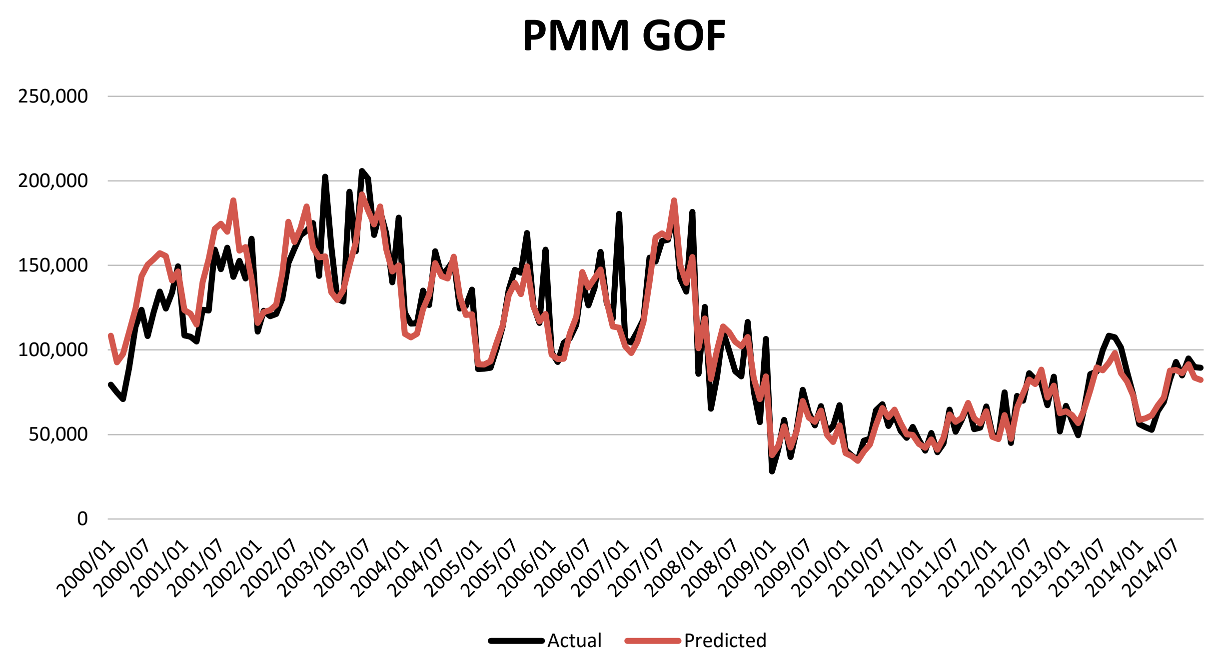
Use of Assumptions as Dials

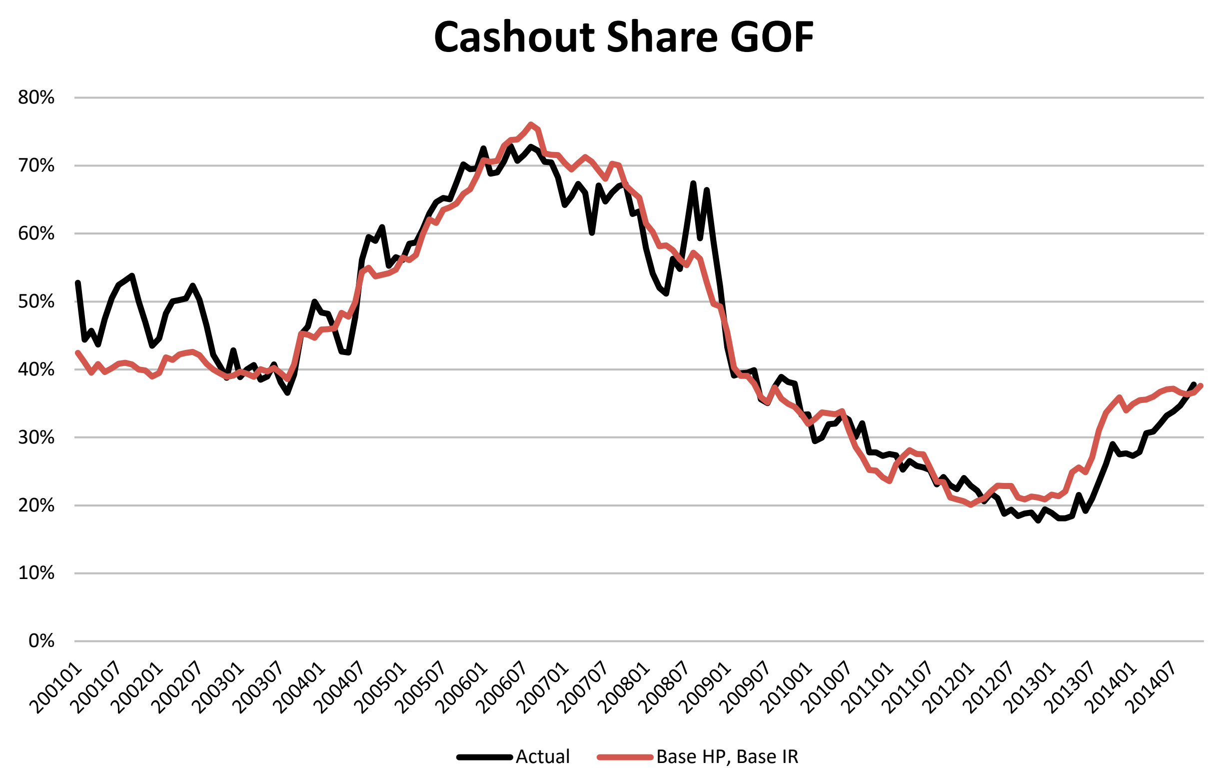
All combined, these four dials – purchase count intercept adjustment, first time borrower share, replenishment rate, refi loan size – give business users flexibility to control projections, as needed.

Model Testing / Validation

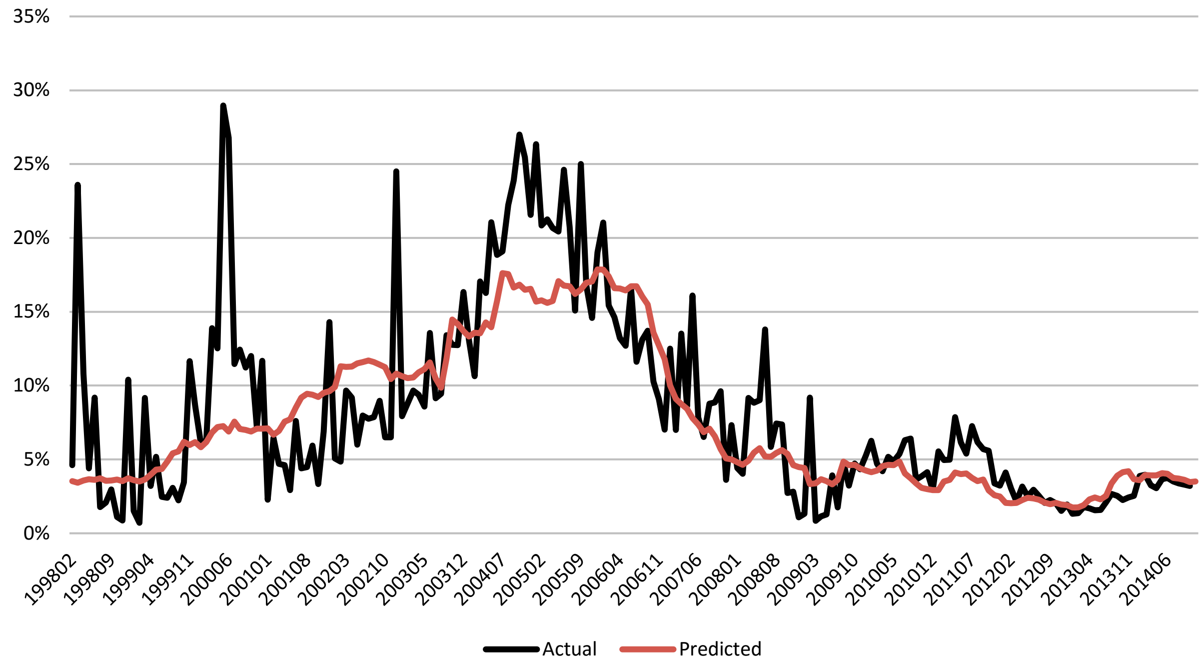
We test the components of the New Loan Acquisition Model by comparing GOF to historical actual data and by observing forecasted values under different HP and IR scenarios.

GOF with Historical Data

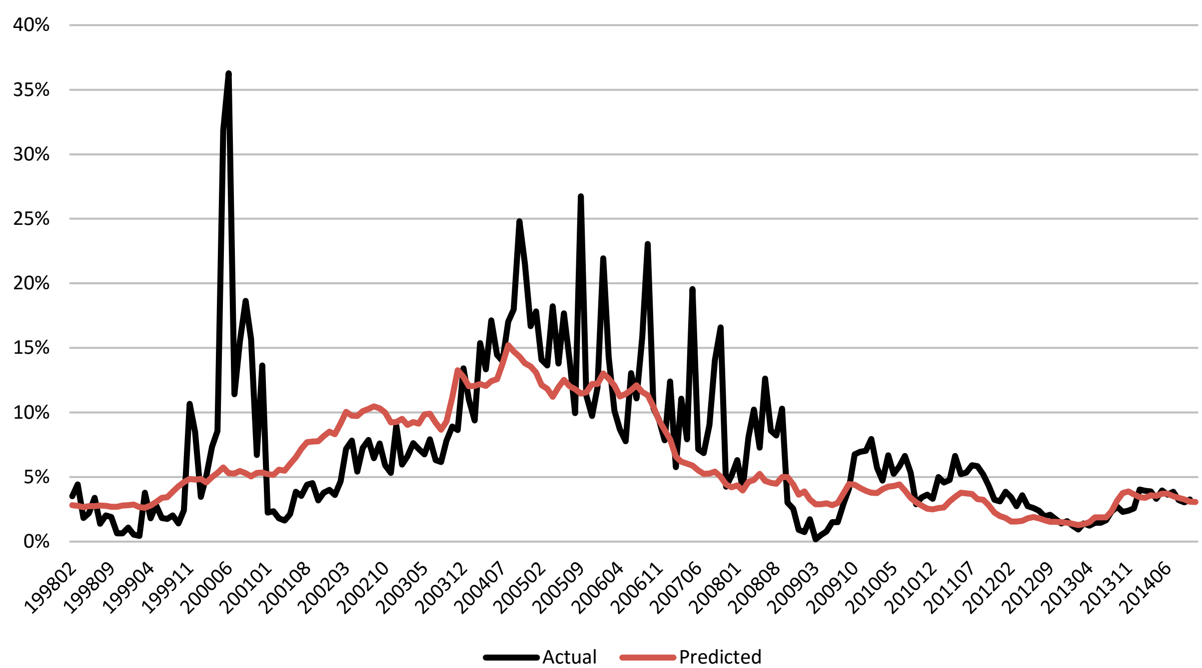




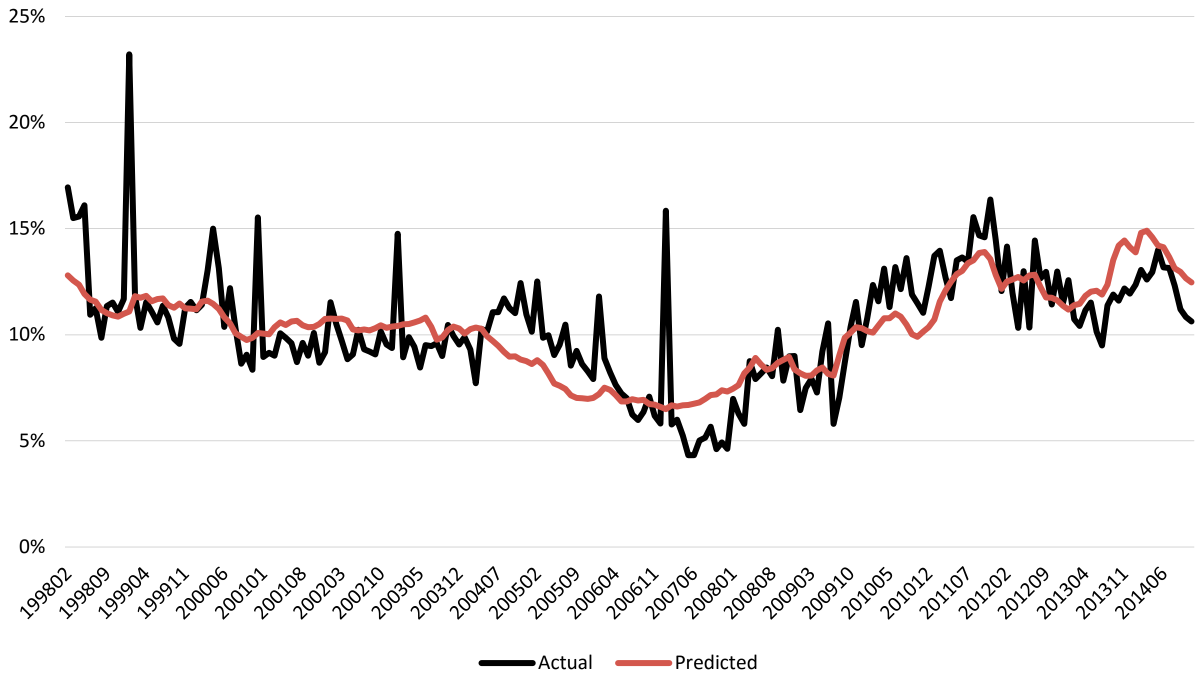
Purchase ARM Share GOF



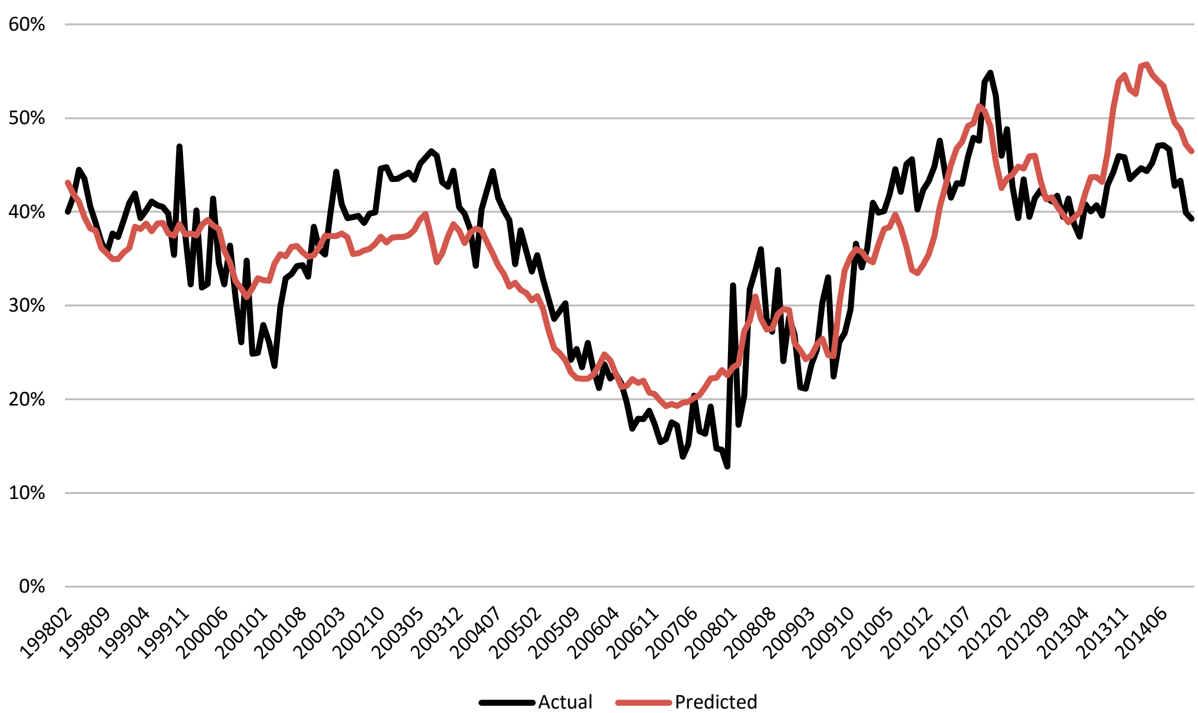
Refi ARM Share GOF



Purchase FRM15 Share GOF



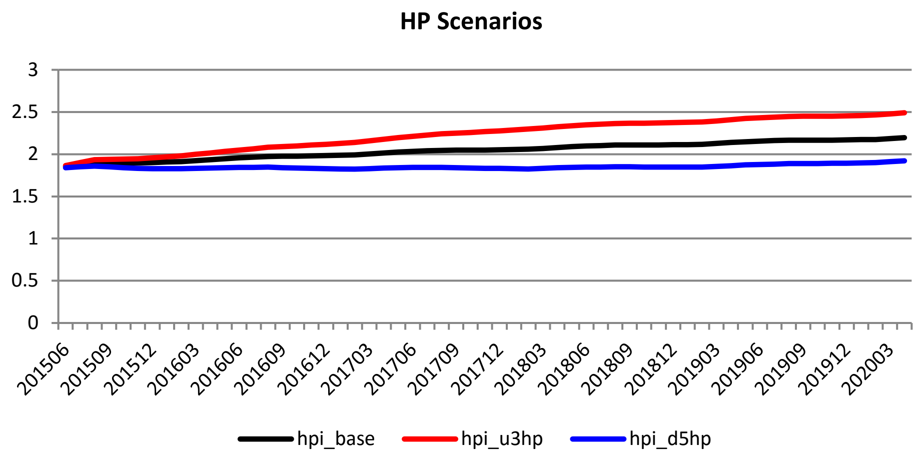
Refi FRM15 Share GOF



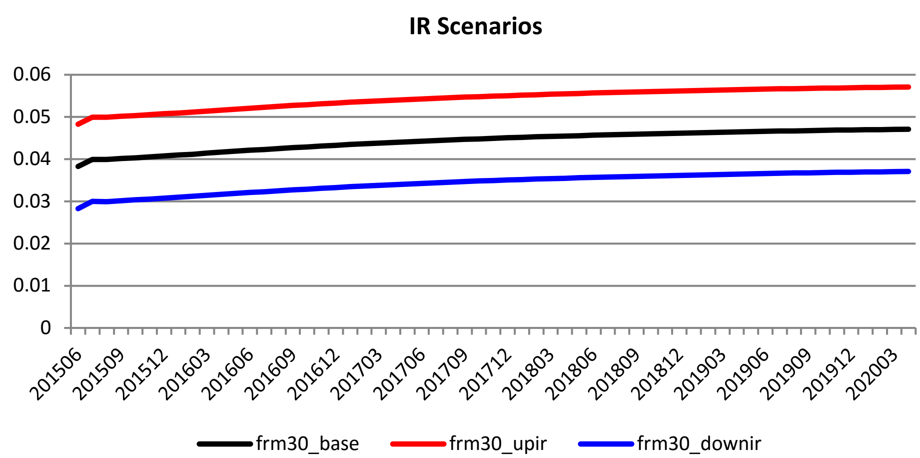
Forecasted Values under different HP and IR scenarios

In addition to GOF test, we test the components of the New Loan Acquisition Model by observing forecasted values under different HP and IR scenarios. Specifically, we choose 5 economic scenarios built from 3 HP scenarios and 3 IR scenarios.

The three HP scenarios are the 201506 LFM production HP base, u3, and d5 scenarios:



The three IR scenarios are the 201502 LFM production IR scenario (the 'base' scenario), an assumption of 100 bps increase, and an assumption of 100 bps:



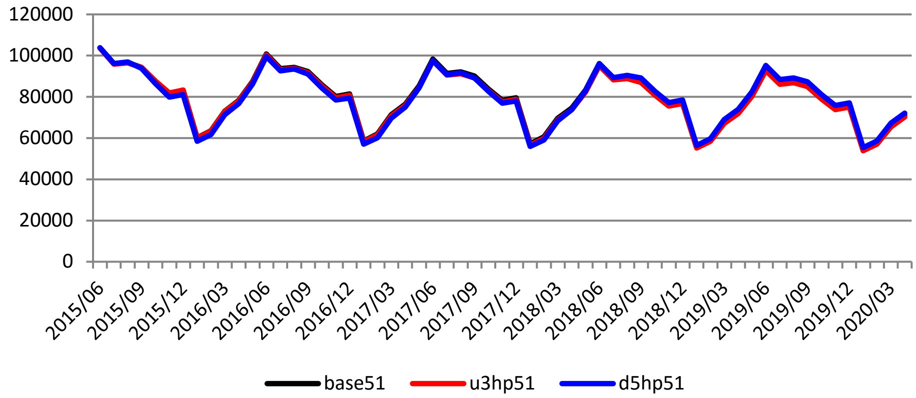
From these HP and IR scenarios, we define 5 economic scenarios[2]:

- Base HP, Base IR

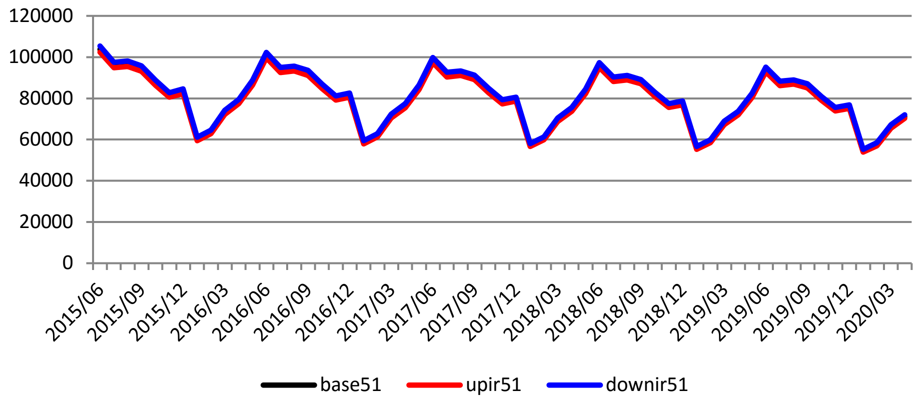
[2] Source: See all five LFM runs from Victor Chang's email at Mon 10/5/2015 3:26 PM.

- Base HP, U IR
- Base HP, D IR
- U3 HP, Base IR
- D5 HP, Base IR

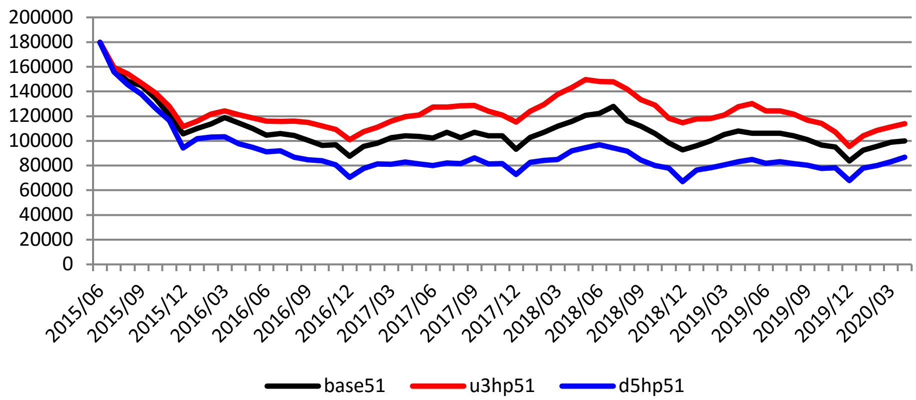
pmm_count Model HP Sensitivity

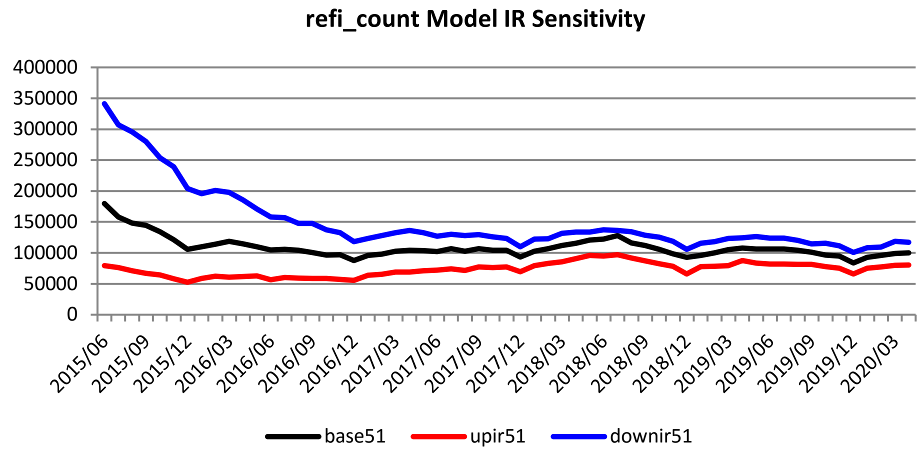


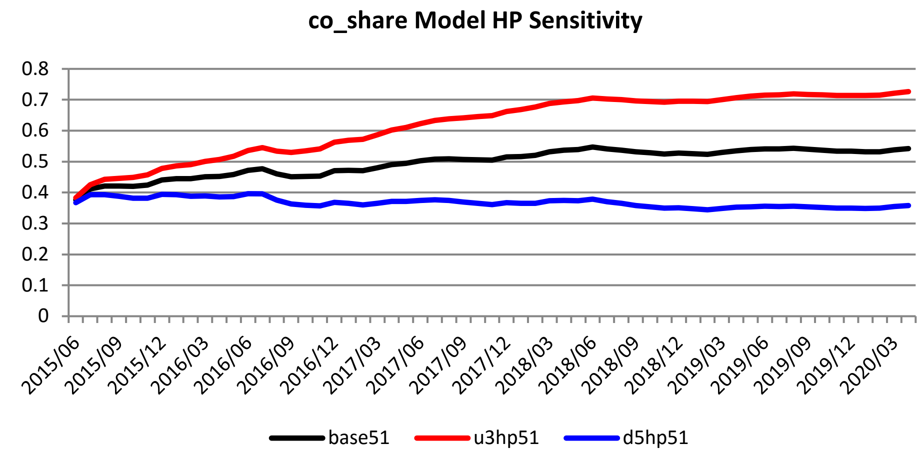
pmm_count Model IR Sensitivity

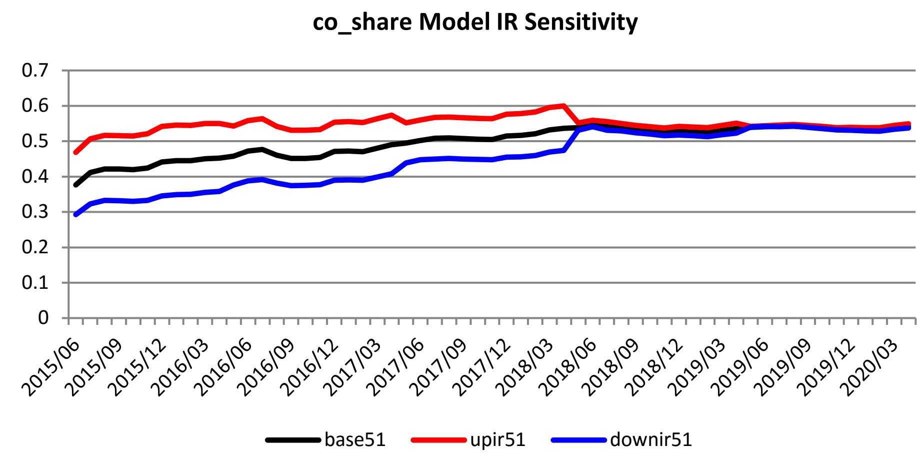


refi_count Model HP Sensitivity

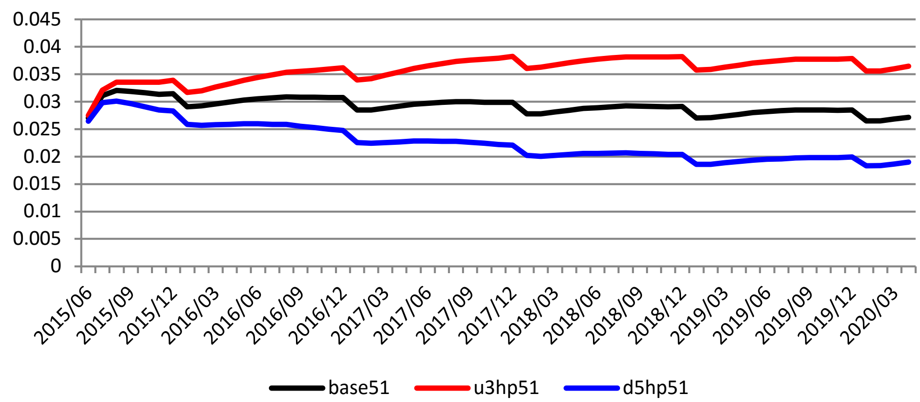



refi_count Model IR Sensitivity
400000
350000
300000
250000
200000
150000
100000
50000
0
2015/06
2015/09
2015/12
2016/03
2016/06
2016/09
2016/12
2017/03
2017/06
2017/09
2017/12
2018/03
2018/06
2018/09
2018/12
2019/03
2019/06
2019/09
2019/12
2020/03
base51
upir51
downir51

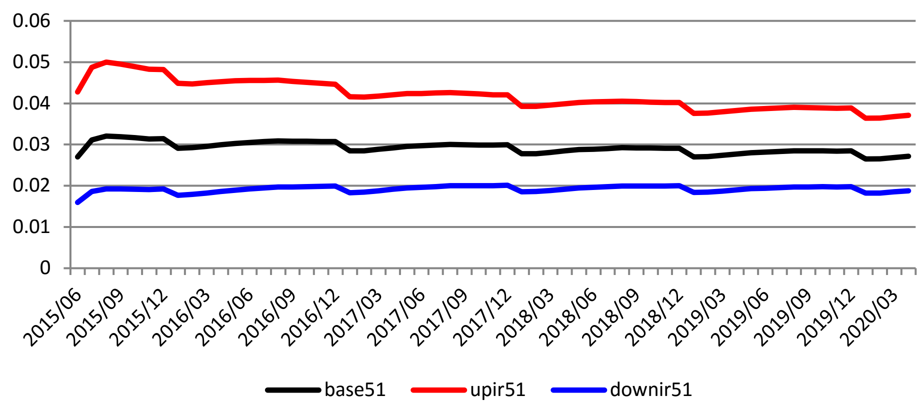

co_share Model HP Sensitivity
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2015/06
2015/09
2015/12
2016/03
2016/06
2016/09
2016/12
2017/03
2017/06
2017/09
2017/12
2018/03
2018/06
2018/09
2018/12
2019/03
2019/06
2019/09
2019/12
2020/03
base51
u3hp51
d5hp51


co_share Model IR Sensitivity
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2015/06
2015/09
2015/12
2016/03
2016/06
2016/09
2016/12
2017/03
2017/06
2017/09
2017/12
2018/03
2018/06
2018/09
2018/12
2019/03
2019/06
2019/09
2019/12
2020/03
base51
upir51
downir51

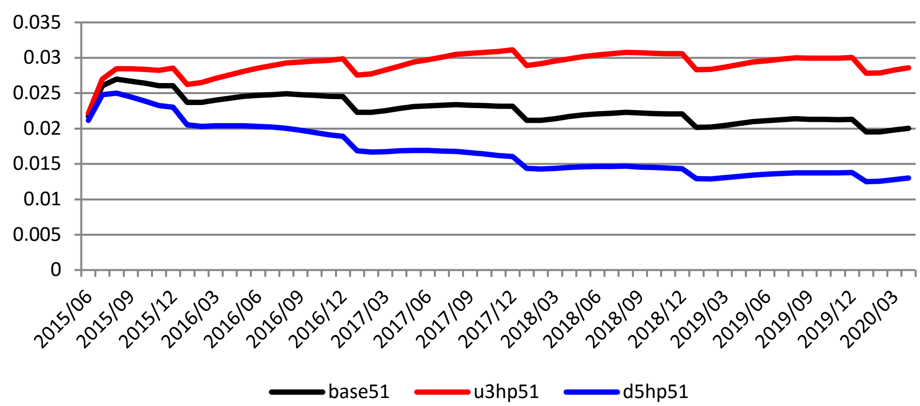
pmm_arm_share Model HP Sensitivity

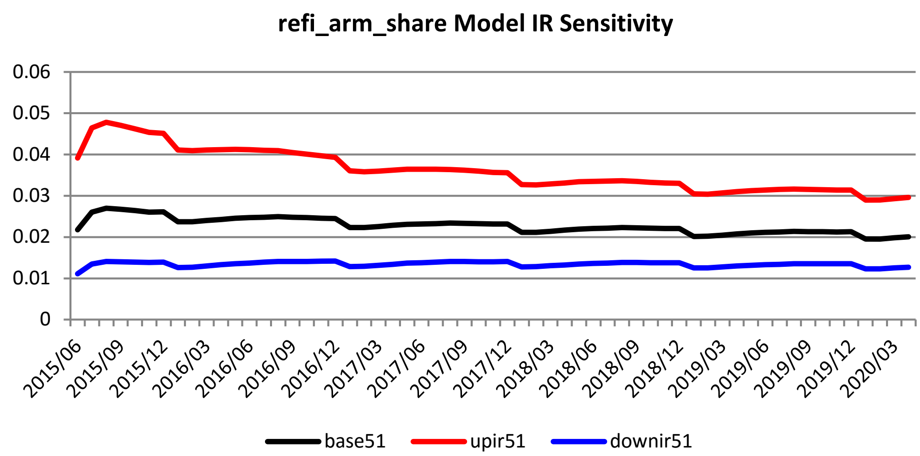


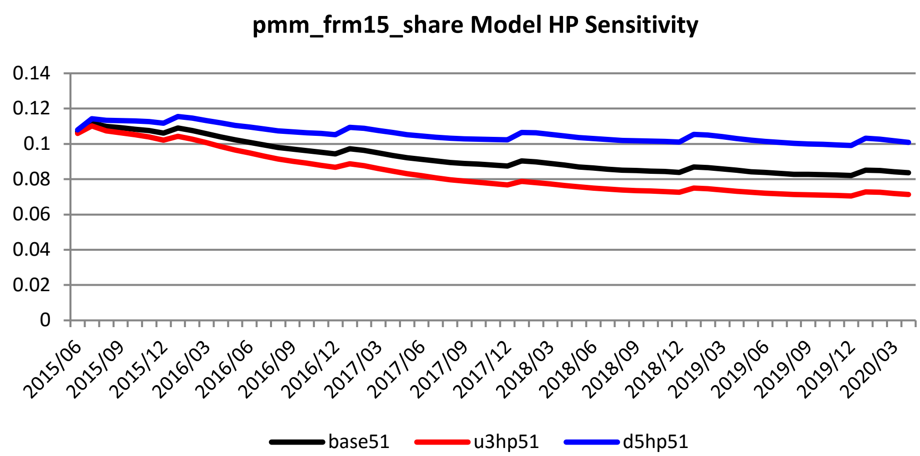
pmm_arm_share Model IR Sensitivity

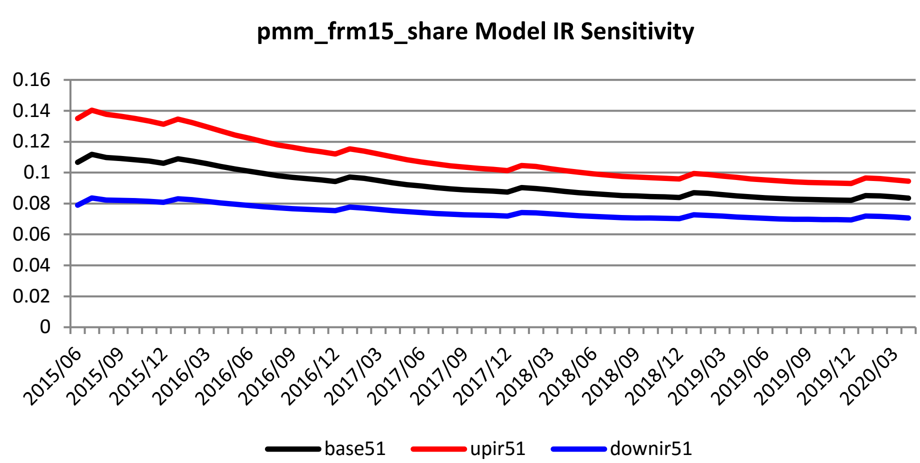


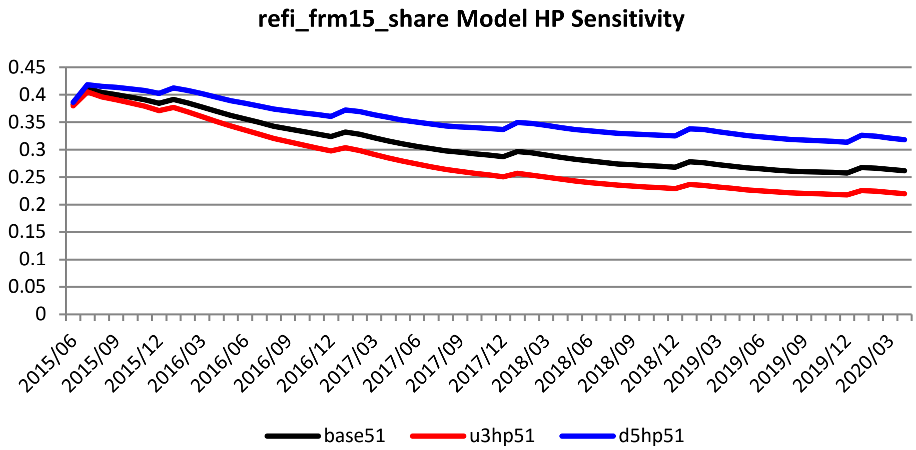
refi_arm_share Model HP Sensitivity

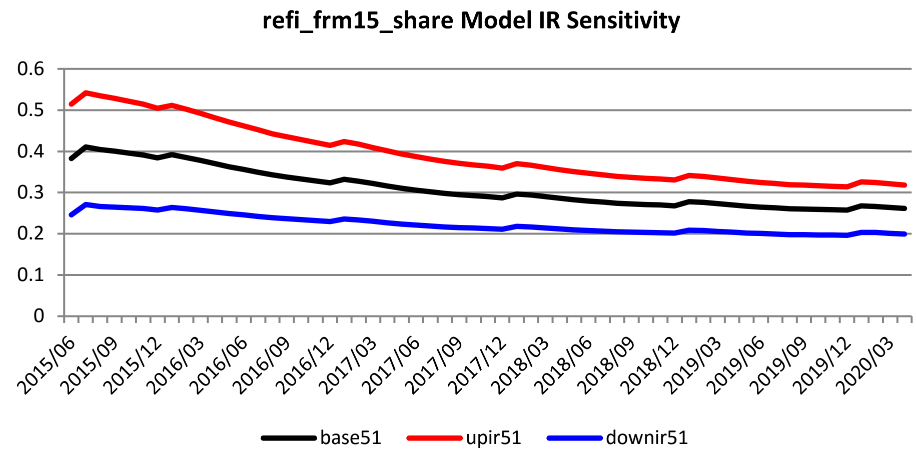



refi_arm_share Model IR Sensitivity
0.06
0.05
0.04
0.03
0.02
0.01
0
2015/06
2015/09
2015/12
2016/03
2016/06
2016/09
2016/12
2017/03
2017/06
2017/09
2017/12
2018/03
2018/06
2018/09
2018/12
2019/03
2019/06
2019/09
2019/12
2020/03
base51
upir51
downir51


pmm_frm15_share Model HP Sensitivity
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
2015/06
2015/09
2015/12
2016/03
2016/06
2016/09
2016/12
2017/03
2017/06
2017/09
2017/12
2018/03
2018/06
2018/09
2018/12
2019/03
2019/06
2019/09
2019/12
2020/03
base51
u3hp51
d5hp51


pmm_frm15_share Model IR Sensitivity
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
2015/06
2015/09
2015/12
2016/03
2016/06
2016/09
2016/12
2017/03
2017/06
2017/09
2017/12
2018/03
2018/06
2018/09
2018/12
2019/03
2019/06
2019/09
2019/12
2020/03
base51
upir51
downir51





With parallel shift of IR at book date, frm30_1yrgr converges after 1 year, frm30_2yrgr converges after 2 years, frm30_3yrgr converges after 3 years, etc. Since frm30_3yrgr has largest parameter in CO Share equation, CO Share prediction also converges after 3 years.

Model Limitations

Similar to the experiences of many financial models, after the 2007-2009 financial crisis, previous historical relationships among variables tends to break down due to factors that are difficult to capture, including tighter lending standards and changes in borrower behaviors and government programs (Hamilton 2015). The PTC related variables in PMM model reflect modeler's view of future environment, which is yet to be tested in reality.

Regarding Refi, a simple formula involving PMM forecast may be subject to compounding error.

There is ample room for improvement on the model specifications and on assumptions, which we continue to investigate on an-ongoing basis.

Reviewed by:
Date:

Model Parameter Overrides

The PMM model may be replaced, at the discretion of the user, with the PMM projection from ESR. This requires an agreement between ESR and the user to ensure timely and accurate PMM projections in a format that may be consumed by the implementation of the new loan acquisition models.

Reviewed by:
Date:

Conclusion

This model provides a way to estimate historical PMM and Refi mortgage originations and a forecast of future mortgage originations so that the company can estimate mortgage acquisitions. The current proposed specification is a considerable enhancement over the previously proposed LFM5.0 in that (1) it has transparent connection between economic environment and forecasted activity (2) it links Refi UPB and LTV to prepay profile.

As part of any macro or aggregate forecasting, it is often necessary to combine pure modeling elements with management assumptions or policy change. LFM5.1 model allow user to adjust forecasts to account for changes in outlook and align with other groups within the company (ESR/SFF Revenue) without resorting to overrides.

References

Fout, Hamilton (2015). “Mortgage Market Refi Originations Forecast Model”. Whitepaoer.

Appendices

I. Data Dictionary

PMM Model Variables

Variable	Interpretation	Computation

hp3yr_ptc_us1	3 year peak-to-current HP growth	array monthly_array{37} hpi1-hpi37;
		array growth{37} g1-g37;
		do i = 1 to 37;
		growth[i] = monthly_array[1] / monthly_array[i];
		end;
		hp3yr_ptc_us = min(min(of g2-g37) - 1 , 0);
		
		hp3yr_ptc_us1 = hp3yr_ptc_us;
		
		if act_dte >= '01FEB2010'd then do;
		
		hp3yr_ptc_us1 = -0.18119;
		
		end;

hp3yr_ptc_recov_us	3 year peak-to-current HP recovery	hp3yr_ptc_recov_us = hp3yr_ptc_us - hp3yr_ptc_us1;

affordability_index_f30	FRM30 affordability index	target_dti = 0.28;
		
		affordable_pmt = (income / 12) * target_dti;
		
		affordable_hp_frm30 = mort(. , affordable_pmt , frm30 / 12 , 360) / 0.8;
		
		med_hp = &index_hp * (hpi / &index_hpi);
		
		affordability_index_f30 = affordable_hp_frm30 / med_hp;

md_ttl_1	Seasonal Dummy for January	1 if month=January;0 otherwise
md_ttl_2	Seasonal Dummy for Febuary	1 if month=Feburary;0 otherwise
md_ttl_3	Seasonal Dummy for March	1 if month=March;0 otherwise

md_ttl_4	Seasonal Dummy for April	1 if month=April;0 otherwise
md_ttl_5	Seasonal Dummy for May	1 if month=May;0 otherwise
md_ttl_6	Seasonal Dummy for June	1 if month=June;0 otherwise
md_ttl_7	Seasonal Dummy for July	1 if month=July;0 otherwise
md_ttl_8	Seasonal Dummy for August	1 if month=August;0 otherwise
md_ttl_9	Seasonal Dummy for September	1 if month=September;0 otherwise
md_ttl_10	Seasonal Dummy for October	1 if month=October;0 otherwise
md_ttl_11	Seasonal Dummy for November	1 if month=November;0 otherwise
share_ttl	Fannie market share	Assumption from ESR

Cashout Share Model Variables

Variable	Interpretation	Computation
frm30_1yrgr	1 year FRM30 Growth	frm30/lag12(frm30)
frm30_2yrgr	2 year FRM30 Growth	frm30/lag24(frm30)
frm30_3yrgr	3 year FRM30 Growth	frm30/lag36(frm30)
frm30_45_avg	Avg of 4 and 5 year FRM30 Growth	(frm30/lag48(frm30)+frm30/lag60(frm30))/2
Hpi_trend_gap	Difference between HPI and long-term HPI linear trend, where HPI trend is the	hpi - hpi_trend

	linear fit to HPI over the estimation period, indexed to Jan 1996.	

ARM Share Model Variables

Variable	Interpretation	Computation

affordability_index_f30	Ratio between "affordable" home price (assuming FRM30, 28% DTI, and 80% LTV) and median home price	target_dti = 0.28;
		
		affordable_pmt = (income / 12) * target_dti;
		
		affordable_hp_frm30 = mort(. , affordable_pmt , frm30 / 12 , 360) / 0.8;
		
		med_hp = &index_hp * (hpi / &index_hpi);
		
		affordability_index_f30 = affordable_hp_frm30 / med_hp;

arm51_frm30_spread100	spread between ARM 5/1 and FRM 30 rates	(frm30 - arm51) * 100

hp3yr_ttc_us_pre_rec_cap1	maximum hp growth in last 3 years, capped at 0.1 and set to zero post recession	array monthly_array{37} hpi1-hpi37;
		array growth{37} g1-g37;
		do i = 1 to 37;
		growth[i] = monthly_array[1] / monthly_array[i];
		end;
		hp3yr_ttc_us = max(max(of g2-g37) - 1 , 0);
		hp3yr_ttc_us_pre_rec_cap1 = (year(act_dte) <= 2010) * (max(hp3yr_ttc_us - 0.1 , 0));

FRM15 Share Model Variables

Variable	Interpretation	Computation

affordability_index_f30	Ratio between "affordable" home price (assuming FRM30, 28% DTI, and 80% LTV) and median home price	target_dti = 0.28;
		
		affordable_pmt = (income / 12) * target_dti;
		
		affordable_hp_frm30 = mort(. , affordable_pmt , frm30 / 12 , 360) / 0.8;
		
		med_hp = &index_hp * (hpi / &index_hpi);
		
		affordability_index_f30 = affordable_hp_frm30 / med_hp;

affordability_index_f15	Ratio between "affordable" home price (assuming FRM15, 28% DTI, and 80% LTV) and median home price	target_dti = 0.28;
		
		affordable_pmt = (income / 12) * target_dti;
		
		affordable_hp_frm15 = mort(. , affordable_pmt , frm15 / 12 , 180) / 0.8;
		
		med_hp = &index_hp * (hpi / &index_hpi);
		
		affordability_index_f15 = affordable_hp_frm15 / med_hp;

frm15_frm30_spread100	spread between FRM 15 and FRM 30 rates	(frm30 - frm15) * 100

II. Model coefficients/parameters

PMM: dependent variable = ln(PMM)

Variable	**Coefficient**	**t-Value**	**Probt**
Intercept	12.65147	108.6	<.0001
pmm_hp3yr_ptc_us1	6.932429	30.63	<.0001
pmm_hp3yr_ptc_recov_us	2.054711	8.92	<.0001

pmm_affordability_index_f30	0.068303	0.83	0.4071
pmm_md_ttl_1	-0.30978	-10.33	<.0001
pmm_md_ttl_2	-0.25341	-8.6	<.0001
pmm_md_ttl_3	-0.11348	-3.8	0.0002
pmm_md_ttl_4	-0.04343	-1.44	0.1516
pmm_md_ttl_5	0.067552	2.27	0.0247
pmm_md_ttl_6	0.211173	7.16	<.0001
pmm_md_ttl_7	0.137331	4.54	<.0001
pmm_md_ttl_8	0.145802	4.82	<.0001
pmm_md_ttl_9	0.123907	3.95	0.0001
pmm_md_ttl_10	0.050819	1.68	0.0958
pmm_md_ttl_11	-0.01648	-0.54	0.5874
pmm_share_ttl	0.516137	14.06	<.0001

Cashout Model (Rate Incentive Stage): dependent variable = aggregated rate incentive

Variable	**Coefficient**	**t-Value**	**Probt**
Intercept	4.46657	19.54	<.0001
frm30_1yrgr	-0.5154	-1.9	0.0595
frm30_2yrgr	-1.02856	-3.23	0.0015
frm30_3yrgr	-1.9858	-5.86	<.0001

frm30_45_avg	-0.9594	-3.13	0.0021

Cashout Share Model: dependent variable = ln(Cashout Share/(1-Cashout Share))

Variable	Coefficient	t-Value	Probt
Intercept	-0.2305	-8.8	<.0001
rate_incentive	-0.35356	-9.24	<.0001
hpi_trend_gap	2.73678	28.75	<.0001

Purchase ARM Share Model: dependent variable = ln(ARM Share/(1-ARM Share))

Variable	Coefficient	t-Value	Probt
Intercept	-1.24932	-3.33	0.001
affordability_index_f30	-1.68343	-6.13	<.0001
arm51_frm30_spread100	0.56593	4.32	<.0001
hp3yr_ttc_us_pre_rec_cap1	5.51879	6.86	<.0001

Refi ARM Share Model: dependent variable = ln(ARM Share/(1-ARM Share))

Variable	Coefficient	t-Value	Probt
Intercept	-1.16198	-2.59	0.0102
affordability_index_f30	-2.01431	-6.13	<.0001

arm51_frm30_spread100	0.82274	5.28	<.0001
hp3yr_ttc_us_pre_rec_cap1	4.45052	4.63	<.0001

Purchase FRM15 Share Model: dependent variable = ln(FRM15 Share/(1-FRM15 Share))

Variable	**Coefficient**	**t-Value**	**Probt**
Intercept	-4.07079	-31.16	<.0001
affordability_index_f30	-2.35788	-8.16	<.0001
affordability_index_f15	4.80827	10.16	<.0001
frm15_frm30_spread100	0.58323	5.5	<.0001

Refi FRM15 Share Model: dependent variable = ln(FRM15 Share/(1-FRM15 Share))

Variable	**Coefficient**	**t-Value**	**Probt**
Intercept	-3.53036	-24.25	<.0001
affordability_index_f30	-3.70458	-11.48	<.0001
affordability_index_f15	7.22601	13.68	<.0001
frm15_frm30_spread100	1.42188	12.12	<.0001

PMM Loan Size Model: dependent variable = DTI

Variable	**Coefficient**	**t-Value**	**Probt**

Intercept	0.353267	39.81	<.0001
affordability_index_f30	-0.06392	-10.12	<.0001

III. SAS estimation data and code located in pwarehouse-rsas15lp1: /export/appl/bvf_data3_r/ics/devl_rob/extra/acquisitions

For chart templates, see embedded Excel spreadsheet on page 16

Reviewed by:
Date: