Machine Learning in Finance Workshop 2020

AGENCY MBS PREPAYMENT MODEL USING NEURAL NETWORKS

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Columbia Bloomberg Machine Learning in Finance 2020

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David Zhang is a Managing Director and Head of Securitized Products Research at MSCI. His team is responsible for developing models and analytics to support investment analysis, risk management, and regulatory compliance. Before joining MSCI, Dr Zhang was Managing Director and head of Securitized Products modeling at Credit Suisse for more than a decade. At Credit Suisse he was responsible for supporting risk, regulatory and client analytics as well as sales/trading quantitative strategies. Dr Zhang's group developed one of the most widely used MBS models by fixed income institutional investors. Their work was consistently awarded top ranking by various industry and client surveys, including Institutional Investor All-America Research Team ranking in Agency prepayment. They also won the award for best paper by the American Real Estate Society for research on effectiveness of government mortgage programs The regulatory projects Dr Zhang lead at Credit Suisse included developing models for CCAR and PPNR (Pre-Provision Net revenue), Dodd-Frank IHC (Intermediate Holding Company) and related VaR, RWA and RBPL modeling, and FRTB (Fundamental Review of Trading Book). Prior to Credit Suisse, Dr Zhang worked at FreddieMac, CIBC Oppenheimer, and University of Chicago. He holds leadership positions at PRMIA (Professional Risk Management International Association) and GCREC (Global Chinese Real Estate Congress). He is a frequent speaker at industry and academic conferences, and his research on risk, financial modeling and real estate has been published in many academic journals. Dr Zhang has a Ph.D. from Princeton University.

SUMMARY: NEURAL NETWORKS AGENCY MBS PREPAYMENT MODEL

Why a machine learning model for Agency MBS?

- Prepayment is a highly complex and non-linear process with many idiosyncratic risk factors, among the most complex financial models
- Recent development in computational software and hardware enable us to make significant advancement in AI prepayment models
- Machine learning models have excelled in many areas, such as image recognition, natural language processing, fraud detection, etc.

What is the model and what have we learned?

- Deep neural network model applied to pool level agency MBS prepayment data, compared with MSCI1 (the human model)
- Results show the deep learning model is able to capture very complex prepayment patterns and signals with extremely high computational efficiency

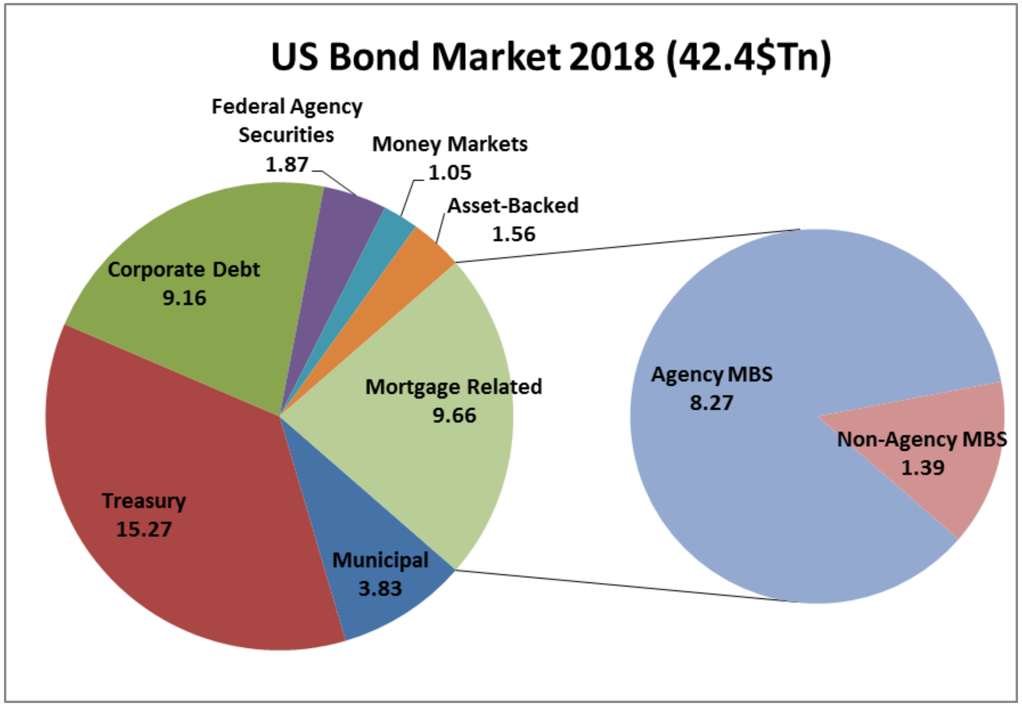
MACHINE LEARNING IN FINANCE

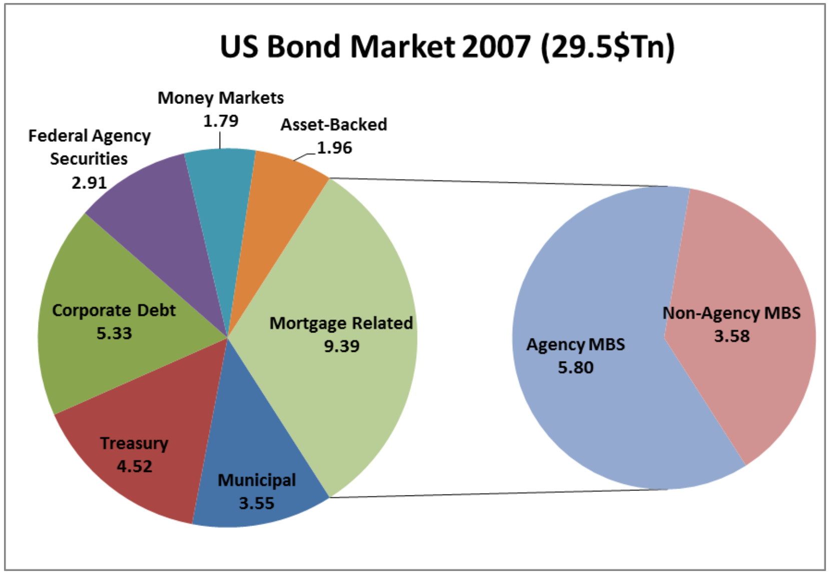
- Consumer credit risk models via Machine-Learning Algorithms (Dr. Andrew Lo, 2010)
  - Using machine-learning model for consumer credit default and delinquency
  - Generalized classification and regression trees
  - Accurately forecasted credit events 3 to 12 months in advance

- Risk and risk management in credit card industry (Dr. Andrew Lo, 2016)
  - Analyzed very large dataset consisting of credit card data from six large banks.
  - Decision trees and random forests model perform better than logistic regression at short time horizon

- Deep learning for mortgage risk (Dr. Kay Giesechke, 2015-2018)
  - Using deep neural network to model mortgage prepayment, delinquency and foreclosure
  - Loan level data
  - Compared NNM with a logit model

US BOND MARKET





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MODELING OBJECTIVE

Forecast prepayment rate for agency RMBS pools

SMM : Single Monthly Mortality Rate

CPR: Conditional Prepayment Rate

Agencies report last month's prepayment speed on the 4th business day of each month.

Prepayment types:

- Rate refinance
- House turnover
- Cash-out
- Curtailment
- Buyout

MORTGAGE PREPAYMENT MODELING: SCIENCE AND CRAFTSMANSHIP

Difficulties with mortgage prepayment modeling

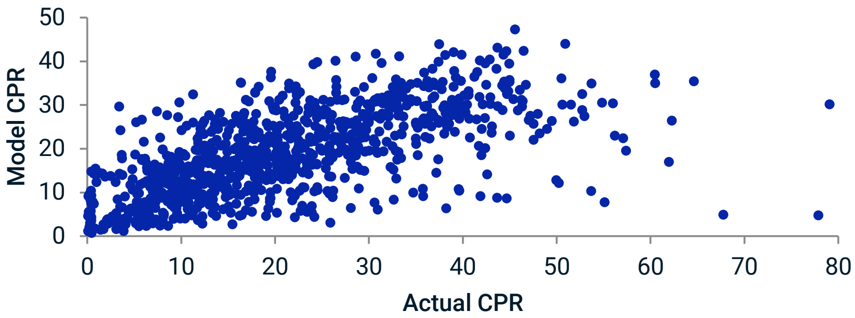
- Large data sets: ~20-2000 G data, Agency MBS covers ~400,000 pools/100^{+}mm loans performance over 20-30 years, pool/loan variables ~30-100

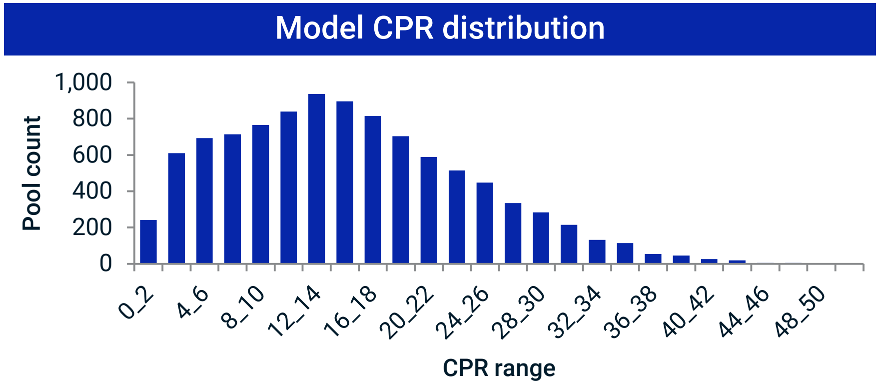
- Multiple, highly non-linear and interactive risk drivers ("layered risk")
  - Loan size vs. prepayment is function of moneyness
  - Age vs. prepayment is function of past moneyness history
  - Loan purpose (refi vs purchase) vs. prepayment is function of origination year
  - ….

- Regime changes
  - Mortgage credit and borrower risk appetite cycles, and business practice affect absolute level and risk drivers for prepayment/default

Agency MBS prepayment

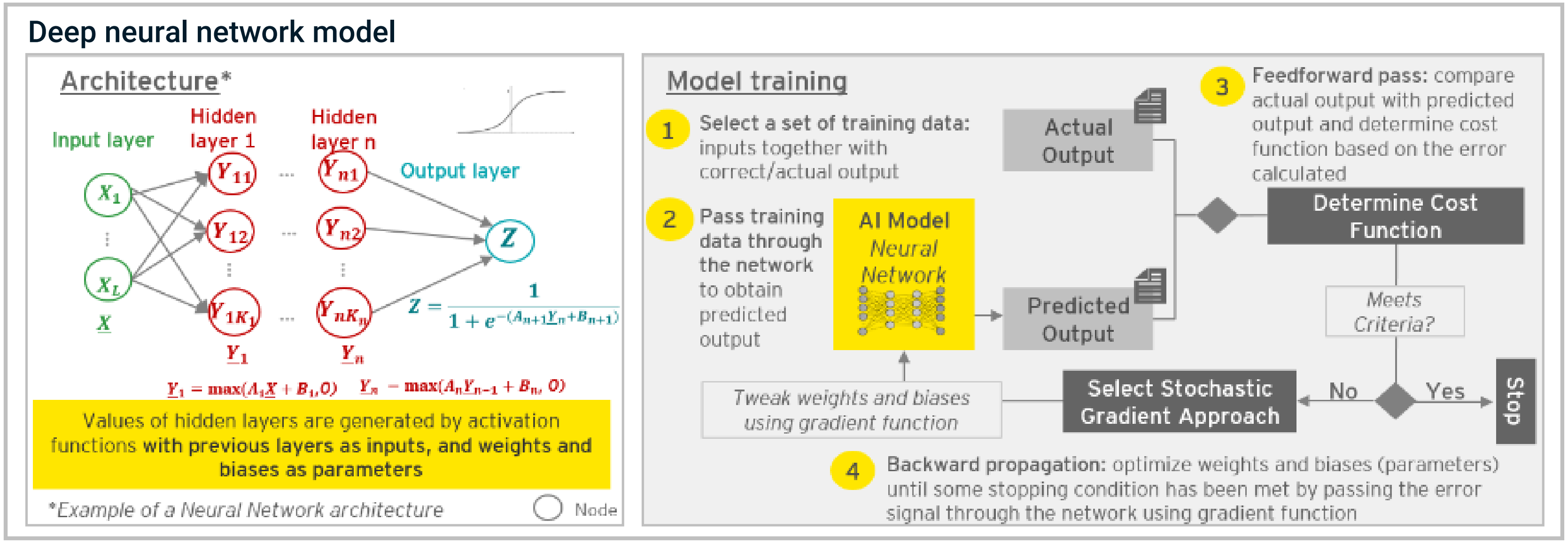
- Complex behaviors
  - 30–100 risk factors: rates, loan size, GEO, purpose, property, HPA….
  - “layered risk”- non-linear interaction (e.g., loan size vs moneyness, purpose vs. origination year, ..)
  - Regime changes: behavior, policy
  - Statistical noises
- Large data set to model
  - 400,000 pools/100m loans, 30yr
- Modelers as craftsman?
  - Idiosyncratic modeler risk





90-100bps ITM FNCL 4s pool speeds

AI agency MBS prepayment model



- Feed forward neural network
  - Applied successfully in many other fields
  - Layers and nodes, hyper-parameters
  - Ensemble techniques, bagging and boosting

- Competing vs. “human” /MSCI production model
  - Forecast accuracy
  - New signals, new discoveries
  - x100-1000 Efficiency gains: 3hrs vs. weeks/months

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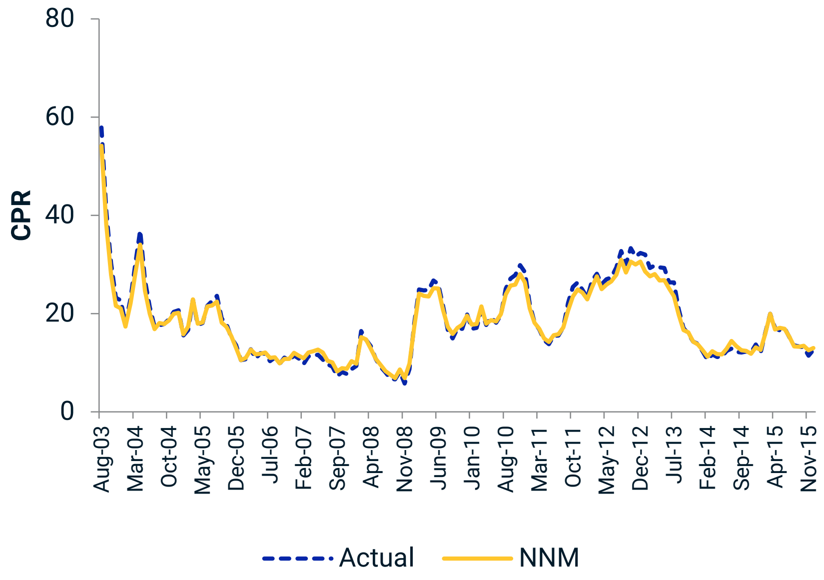
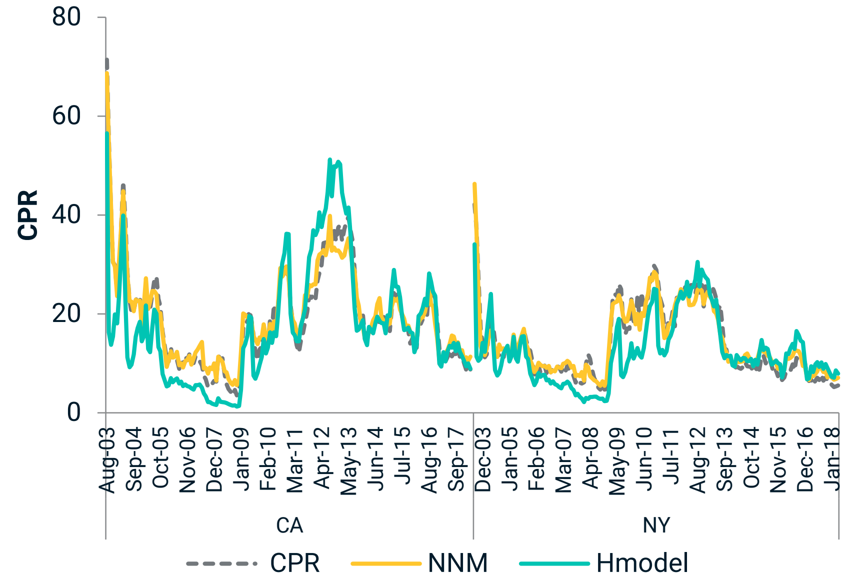
AI vs. “human” models: higher accuracy

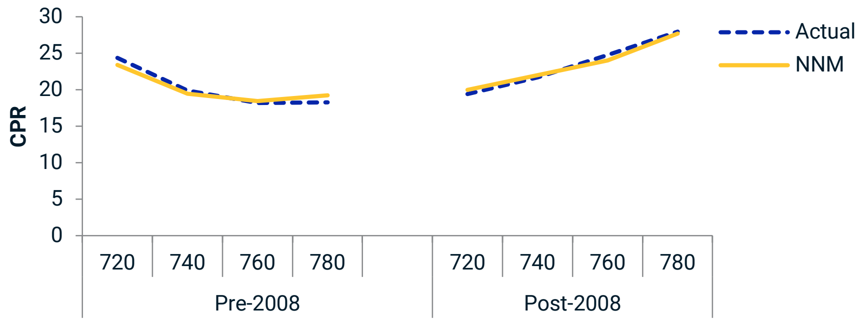




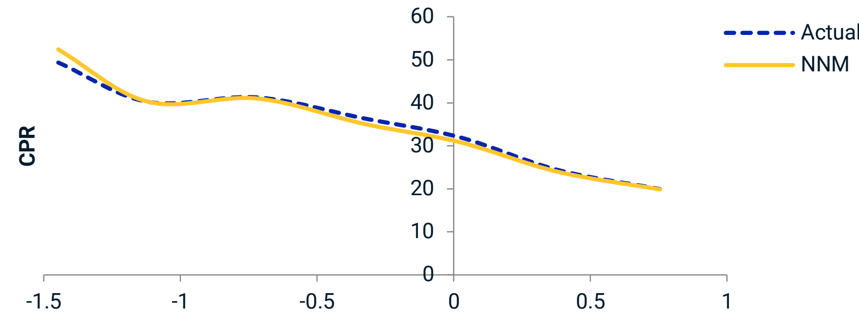
- Higher modeling accuracy
  - Across cohorts and multiple dimensions of risk factors
  - Highly adaptive to high dimensionality and non-linearity

AI vs. “human” models: higher accuracy

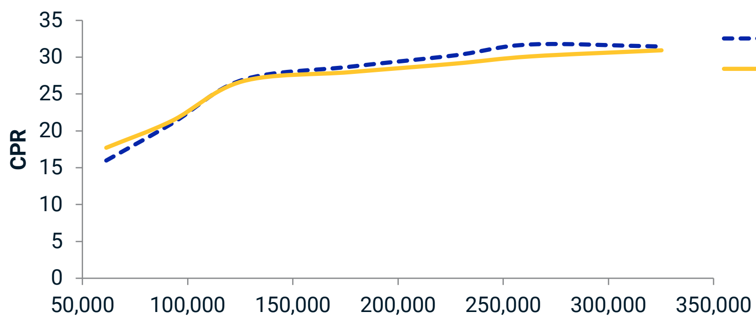
FICO



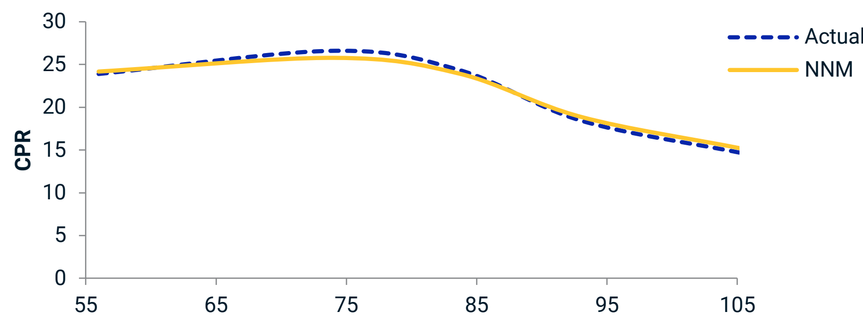
SATO



Current loan size

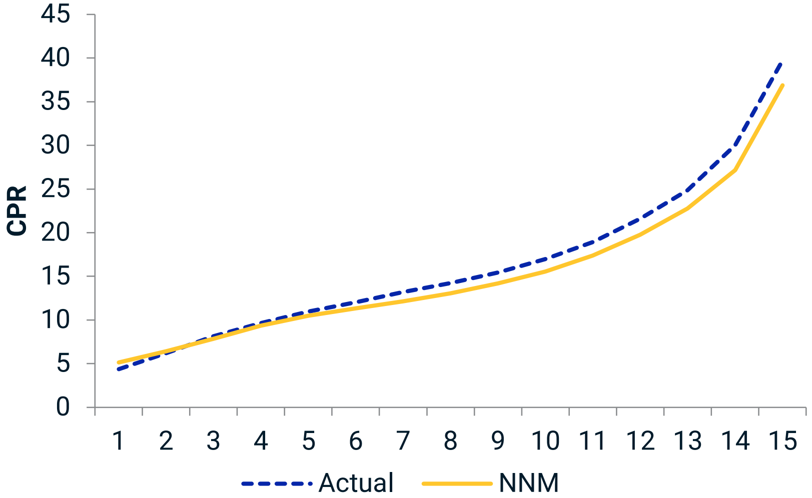


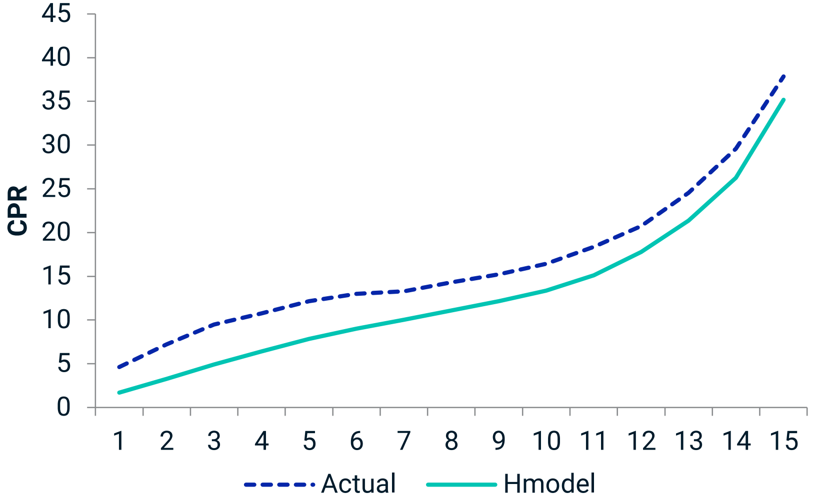
CLTV



AI vs. “human” models: higher accuracy

Ranking based sample error tracking for FNCL 4s





- Higher modeling accuracy
  - Across cohorts and multiple dimensions of risk factors
  - Highly adaptive to high dimensionality and non-linearity

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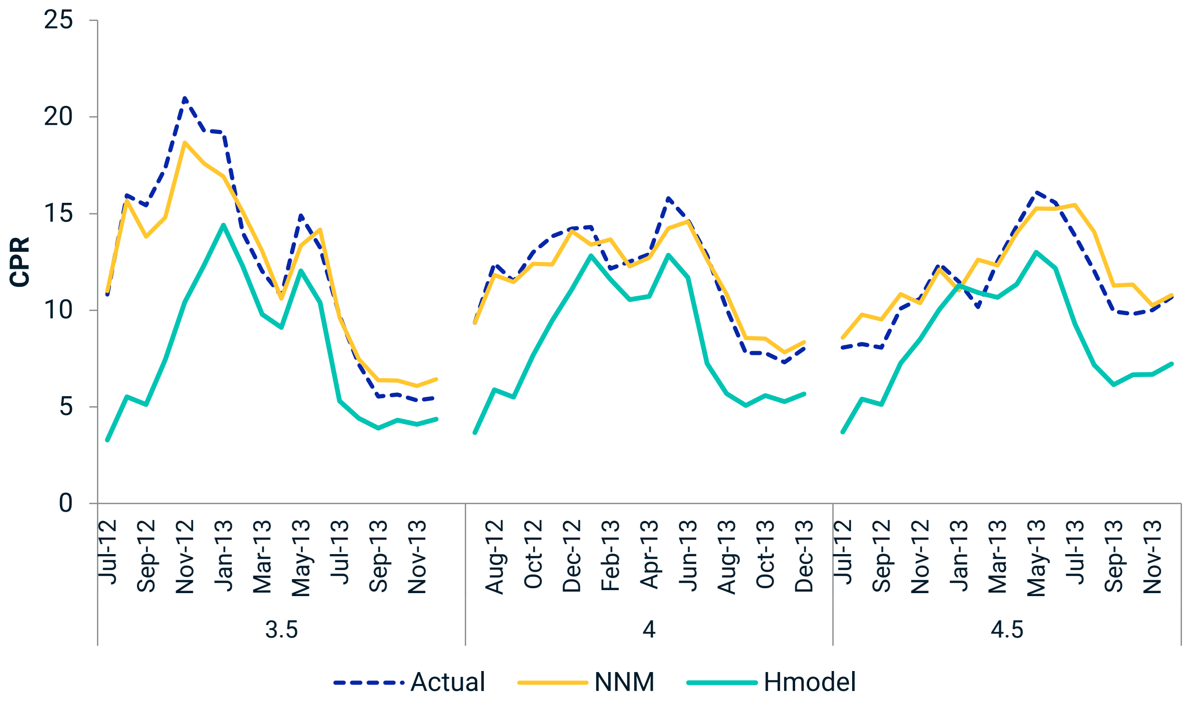
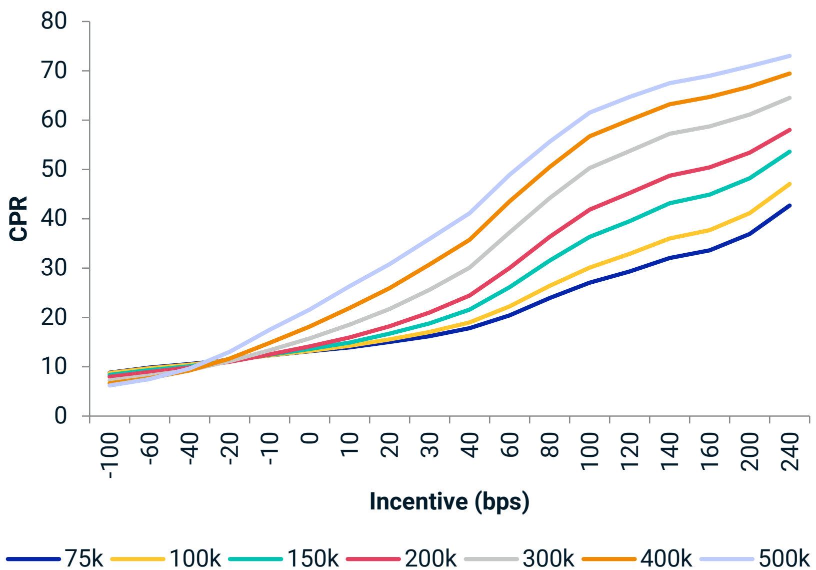
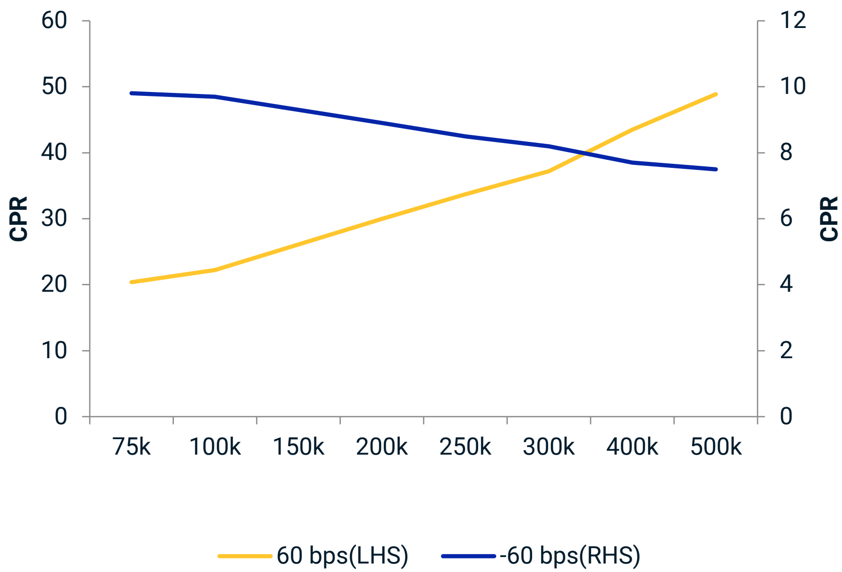
AI vs. "human" models: higher accuracy



- "Media effect"
  - When rates hit historical low, new & lower coupons ramp up faster
  - Highly non-linear behavior and depends on multiple risk factors

AI vs. “human” models: new signals

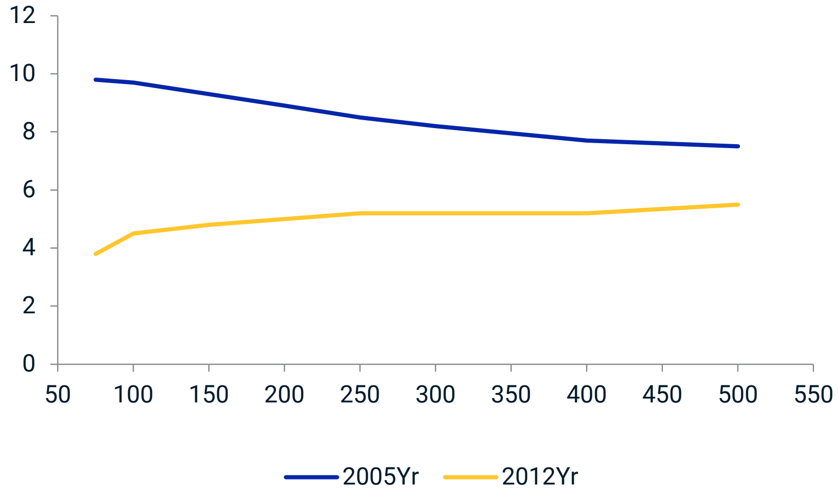




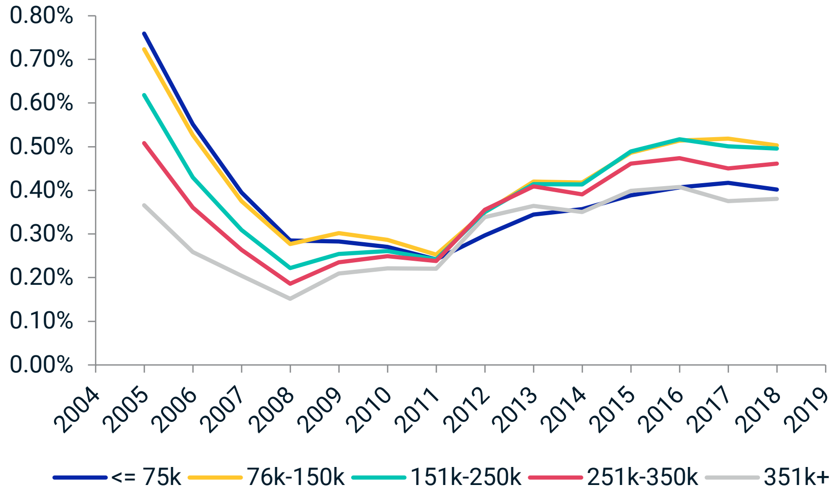
- Accuracy vs overfitting: loan size example
  - Understand sensitivities of risk drivers and economic rationale
  - Apply regularization to penalize overfitting

AI vs. "human" models: new signals

Model speeds for OTM 60bps vs loan size (in thousands)



Housing turnover vs loan size and year*



- Is low loan balance still safe investment for extension risk?
  - Sensitivity tests for the AI model indicate relationship between loan size and housing turnover has flipped after the recession
  - This is verified by Black Knight's proprietary data

* Source: Black Knight, used with permission

CONCLUSION

NN model vs. “Human Model”

- Accurate forecasts and successfully flag prepayment anomalies over the study period
- Accurate model large numbers of risk factors
- Accurate model highly non-linear and interactive risk factors
- Highly efficient modeling process - hundreds times of increases in modeling efficiency
- Was able to find/flag prepayment signals that eluded human models

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Siyu Lin:

Senior Quantitative Analysts, Quantitative Advisory Services , Ernst & Young

Henry Li:

Executive Director, in Quantitative Advisory Services practice, Ernst & Young

Appendix

Exhibit 4: Agency MBS prepayment regimes since 2003

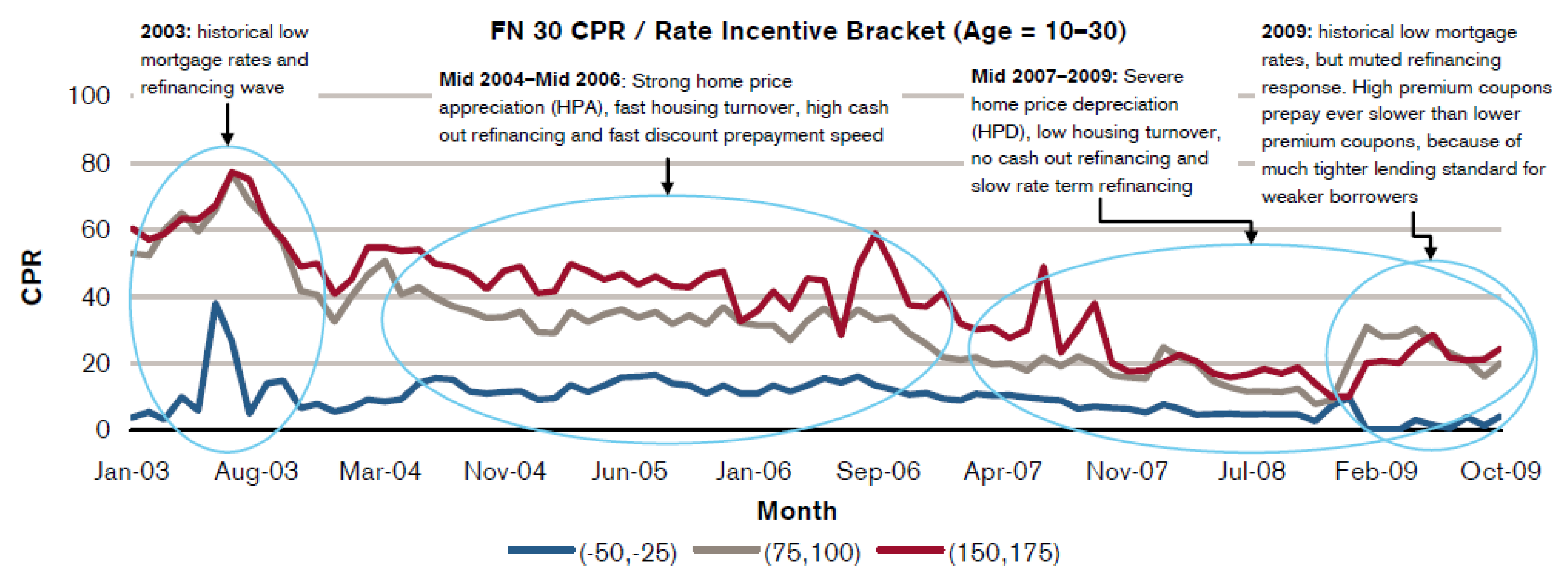
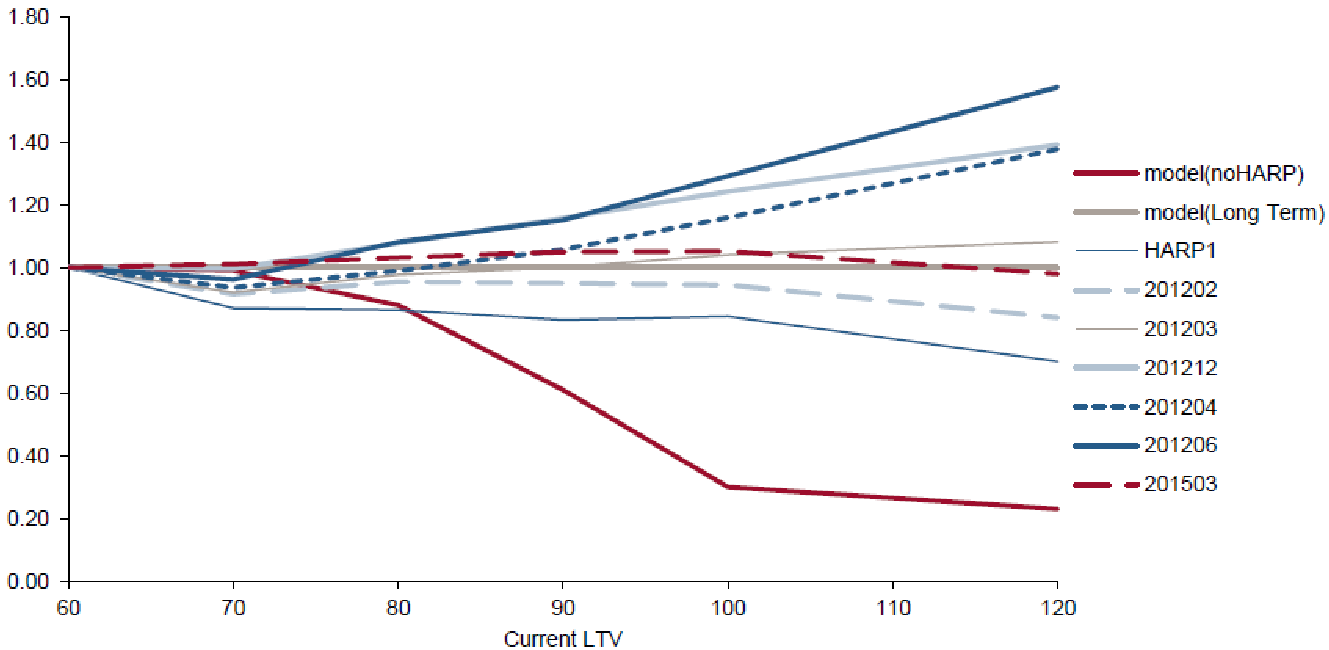


Exhibit 5: HARP CLTV curve history and long term model assumptions

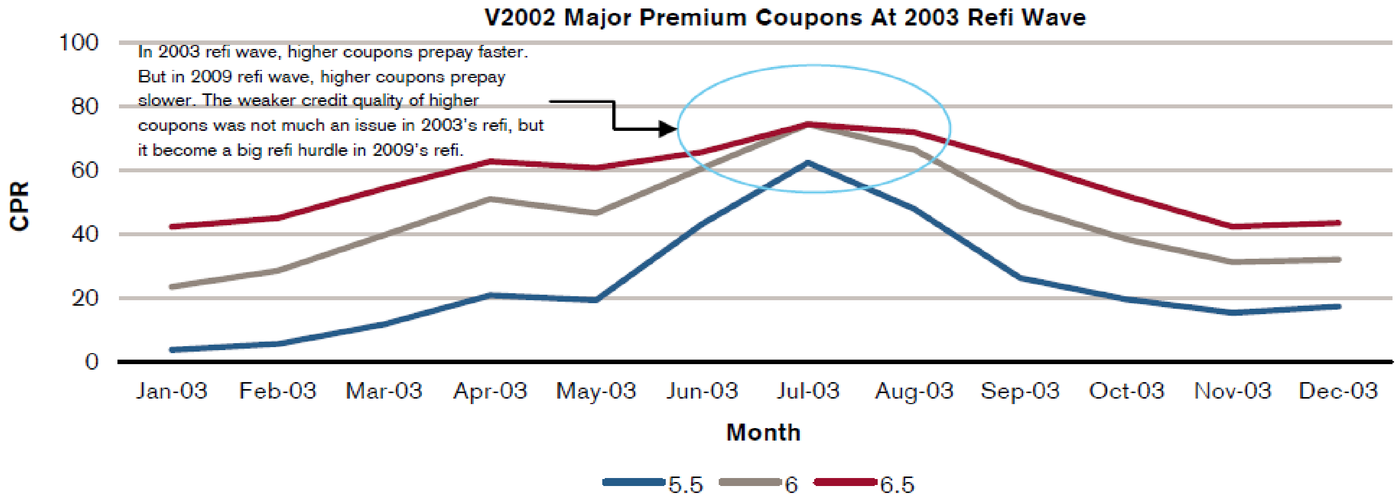
The CLTV curve represents the ratio of refinance speeds across CLTV spectrum, using sub-50 CLTV cohort as benchmark, with all other pool variables (for example, loan size, moneyness, FICO, etc.) holding constant

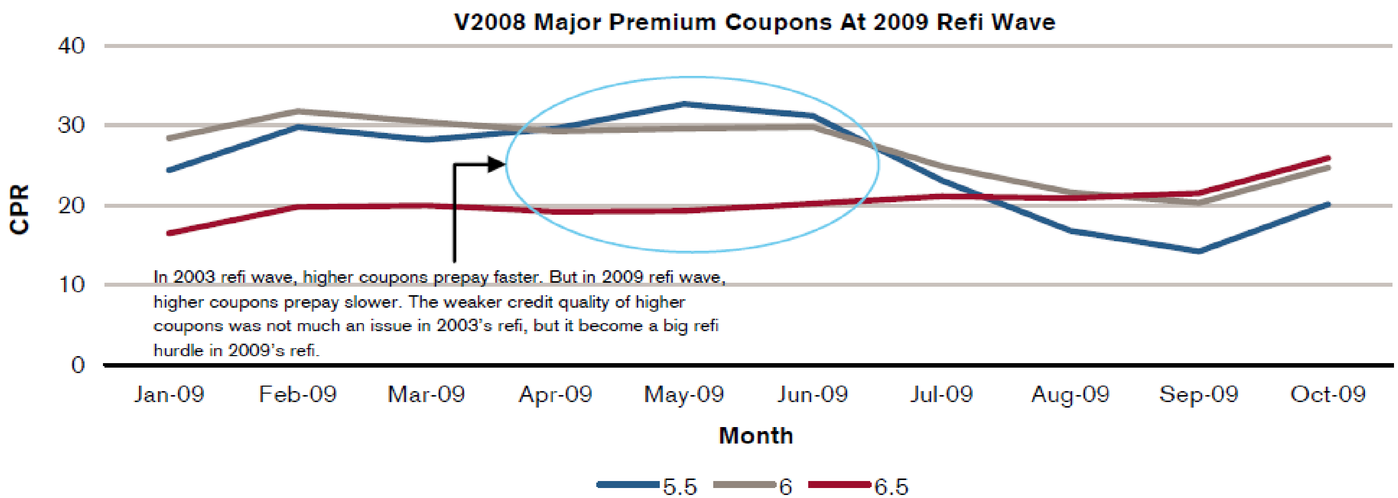


The HARP program caused temporary inversion of the CLTV Prepayment Curve

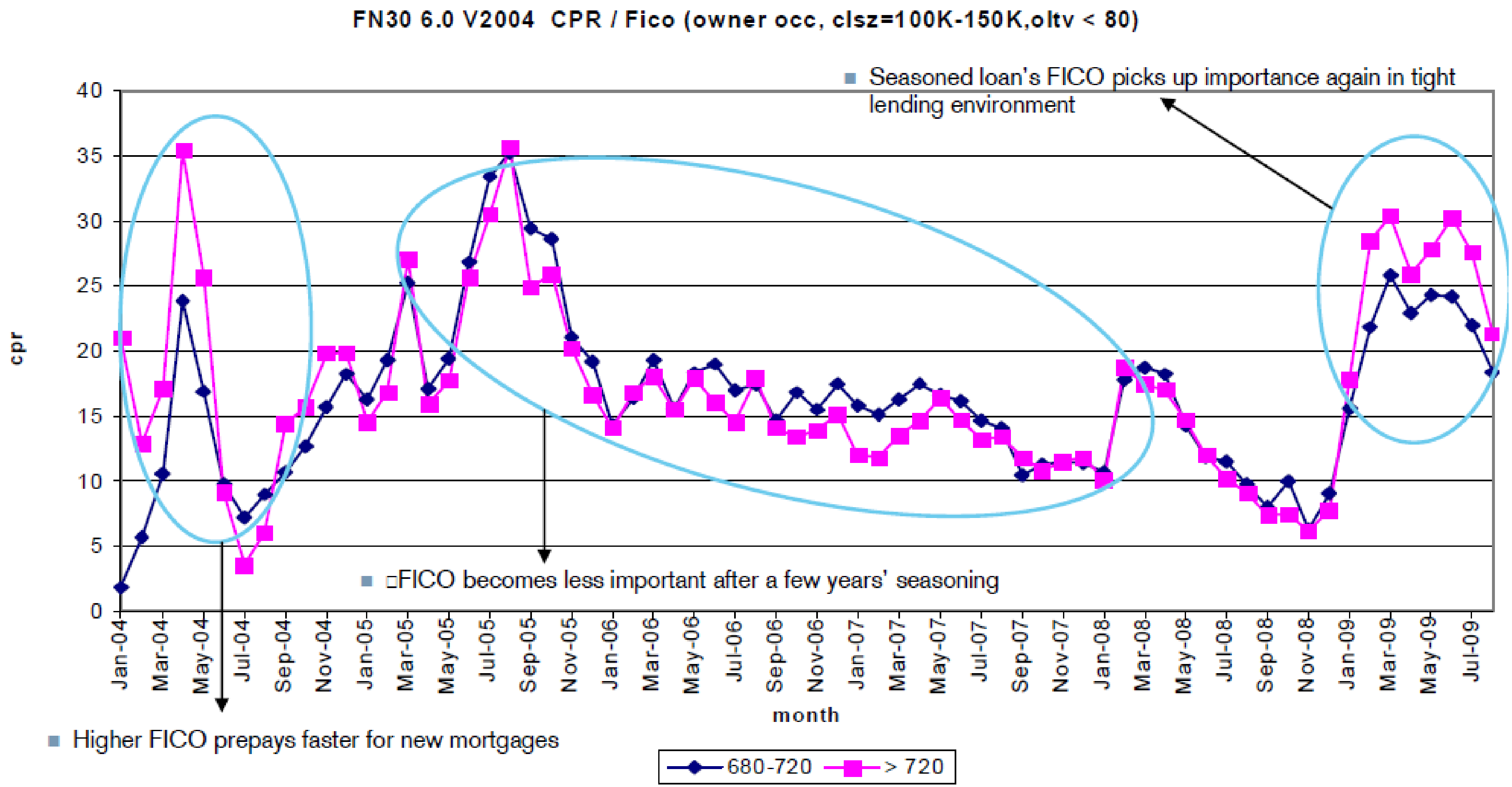
HARP: Home Affordable Refinance Program

MORTGAGE PREPAYMENT MODELING: SCIENCE AND CRAFTSMANSHIP





MORTGAGE PREPAYMENT MODELING: SCIENCE AND CRAFTSMANSHIP



Example of modeling:

Assume ppm (pool, time) = f(X1, X2, X3,…. Xn) …

start by assuming separable risk factor: ppm= f1(x1)*f2(x2)…. Until (often) proven incorrect…

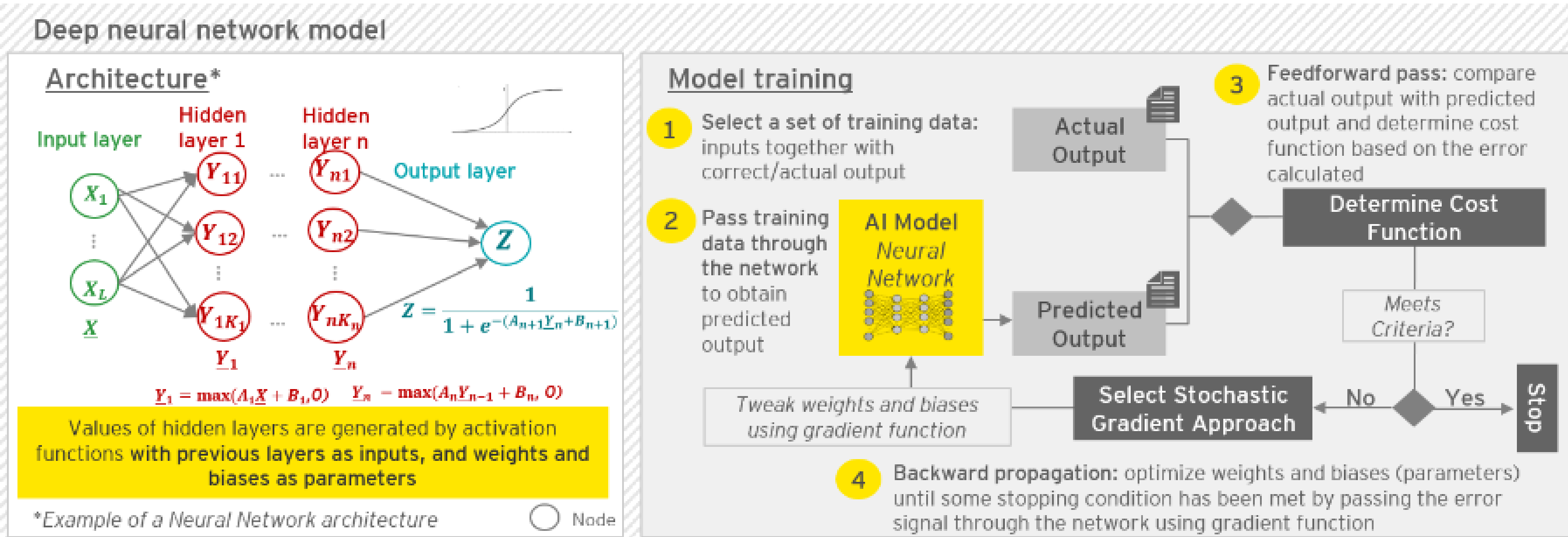
estimating f1(x1) by "building cohort", by bucketing loans/pools for groups of x1, but similar x2, x3….
(this further assumes quasi linear property of x2, x3…. Average(f2(x2) f3(x3)…)= f2(ave(x2))* f3(ave(x3))….

….. Checking overall fit after all Xn are fitted, adding extra variables to deal with non-linear and interactive variables… this often does not lead to convergence …

- Time consuming and non-standard approaches
- Experience and step-by-step / regime-by-regime progress are valued

- Can new techniques of AI modeling provide the much needed disruption?

FEED FORWARD NEURAL NETWORK



Network architecture:

- Layers and nodes
- Hyper-parameters
  - Batch size, number of nodes, learning rate, max-norm constraint, dropout rate

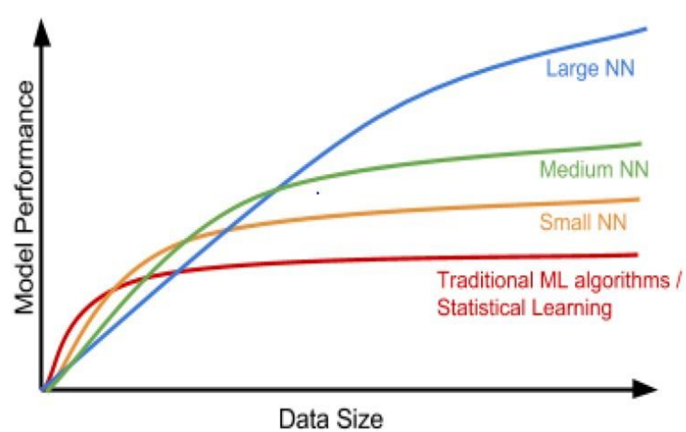
Ensemble techniques:

- Bagging: minimum MSE of different realizations and neural networks
- Boosting: Fine tune a neural network via changing a few hyper-parameters

TRADITIONAL VS.. DEEP MACHINE LEARNING

Identify problems → Set benchmarks → Train models → Compare **performance** → Choose model → Optimize **model** → Deploy

Traditional learning algorithm		**Deep Learning**	
Pros	Cons	Pros	Cons
Works better on smaller data	Hard to scale	state-of-the-art for certain domains, such as computer vision and speech recognition.	require large amount of data.
Financially and computationally cheap	Lack of variability	Perform very well on image, audio, and textual data, Easily updated with new data	Not suitable for classical machine learning problems.
Algorithms are easier to interpret, have more theories to back them up	Labor intensive model maintenance	Versatile architecture and low overhead maintenance	Computationally intensive to train, and they require much more expertise to tune



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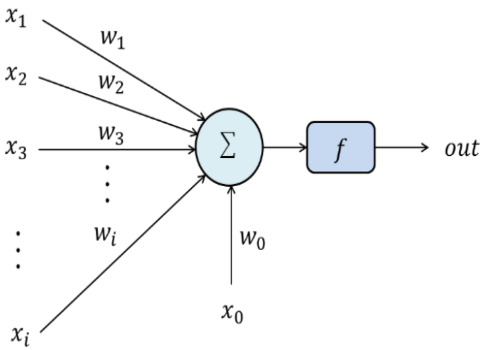
NEURAL NETWORKS MODEL

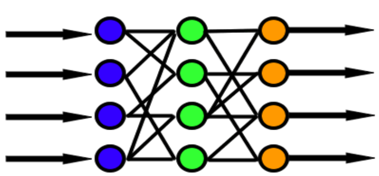
Feed forward neural network (FNN)

the information moves in only forward direction from the input nodes to the output nodes. There are no cycles or loops in the network.;

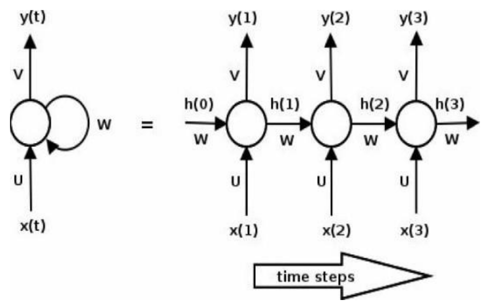
Deep FNN consists of tens of layers and thousands of nodes; the simplest kind of FNN is logistic model



Logistic Model



Feedforward Neural Network



Recurrent Neural Network

Recurrent Neural Network (RNN)

A class of neural networks exploit the historical input sequences. Such inputs could be text, speech, time series, and anything else where the occurrence of an input in the sequence is dependent on the inputs that appeared before it

Motivation: Not all problems can be converted into one with fixed length inputs and outputs, such as text translation, speech recognition or time-series; predictions require a system to store and use context information

The input at time t include both the attributes at t and the intermediate values containing history at t-1.

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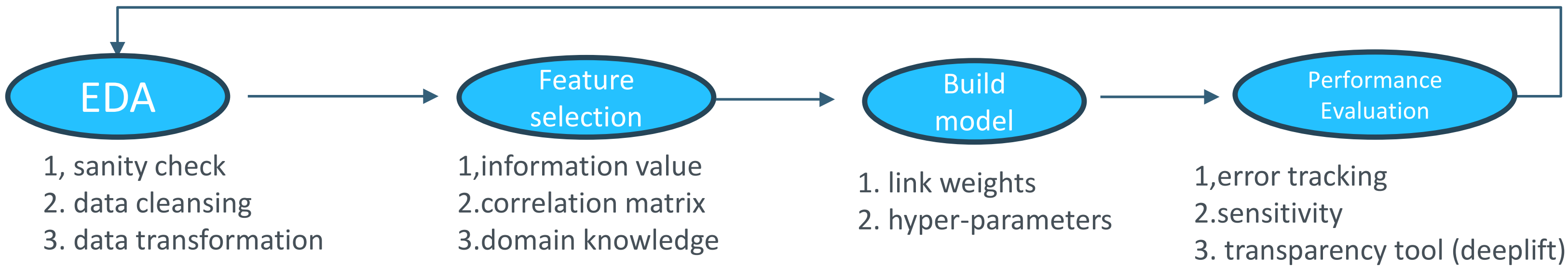
BUILDING NEURAL NETWORK MODEL



Deep neural network fitting

- 2003-2018 30yr agency MBS data (~25G data)
- 30+ input variables: pool attributes, macro-economic variables
- To reduce complexity, we added incentive, 1 regime indicators, and 1 policy indicator (HARP)
- Cost function of RMS error of pool level prepayment
- 1 round of fitting can be completed in ~ 3 hours on a GPU machine

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MODEL DRIVERS

Independent variables	
WALA	Weighted Average Loan Age
WAC	Weighted Average Coupon
CLNSZ	Current Average Loan Size
OLTV	Original Loan to Value
Refi%	Percentage of Refinanced Loans by UPB
SecHome%	Percentage of Second Home Loans by UPB
MultiFamily%	Percentage of Muti Family Loans by UPB
Investor%	Percentage of Investor Loans by UPB
TPO%	Percentage of Third party origination by UPB
AOL	Original Average Loan Size
LNSZ_Q4	Max original loan size
LNSZ_Q3	Max original Loan Size - 3rd Quartile
LNSZ_Q1	Max original Loan Size - 1st Quartile
Geo_CA%	Percentage of California Loans by UPB
Geo_FL%	Percentage of Florida Loans by UPB
Geo_TX%	Percentage of Taxas Loans by UPB
Geo_NY%	Percentage of New York Loans by UPB
Geo_NE%	Percentage of New England Region Loans by UPB
Geo_NO%	Percentage of North Region Loans by UPB
Geo_SO%	Percentage of South region Loans by UPB
Geo_PC%	Percentage of Pacific region Loans by UPB
Geo_AT%	Percentage of Atlantic region Loans by UPB
Geo_NONUS%	Percentage of non-US region Loans by UPB
Seasonality	Calendar month

Derived Variables	
Incentive	WAC - Mortgage Rate(t)
Rolling Incentive	Average Incentive (20month) $\sum_{t=1}^{t=\min(20,wala)} Incentive/\min(20,w$
Loan size dispersion	(LNSZ_Q3-LNSZ_Q1)/AOL
SATO	Spread-at_origination = WAC - Mortgage Rate(0)
HPA	House Price Appreciation (HPI(t)/HPI(0)-1)
HARP-able	and Dec. 2011 2: IssueMonth <= Jun. 2009 and factor date > Dec. 2011
HARP-ed	Refi% = 100 and OLTV > 80 and issueMonth > Jun. 2009
Underwritting standard	0: before 2008, 1: after 2008
Weight	
cBal	Current Balance
Dependent Variable	
Prepayment speed	Prepayment speed in SMM

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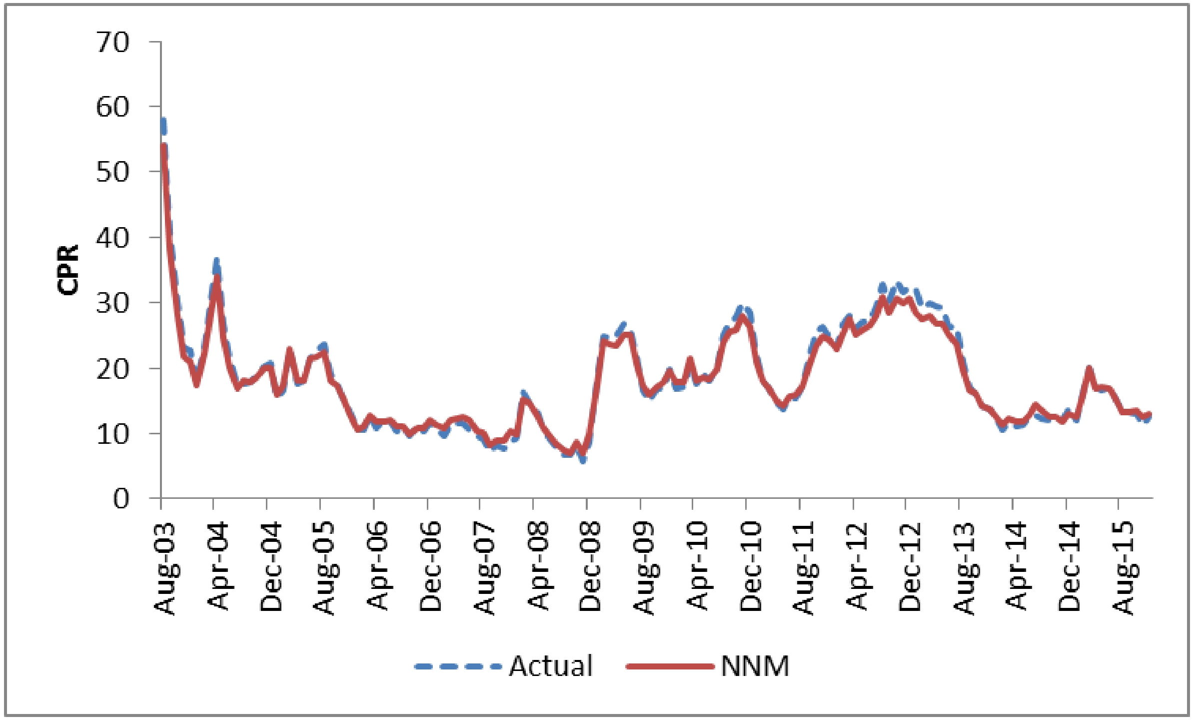
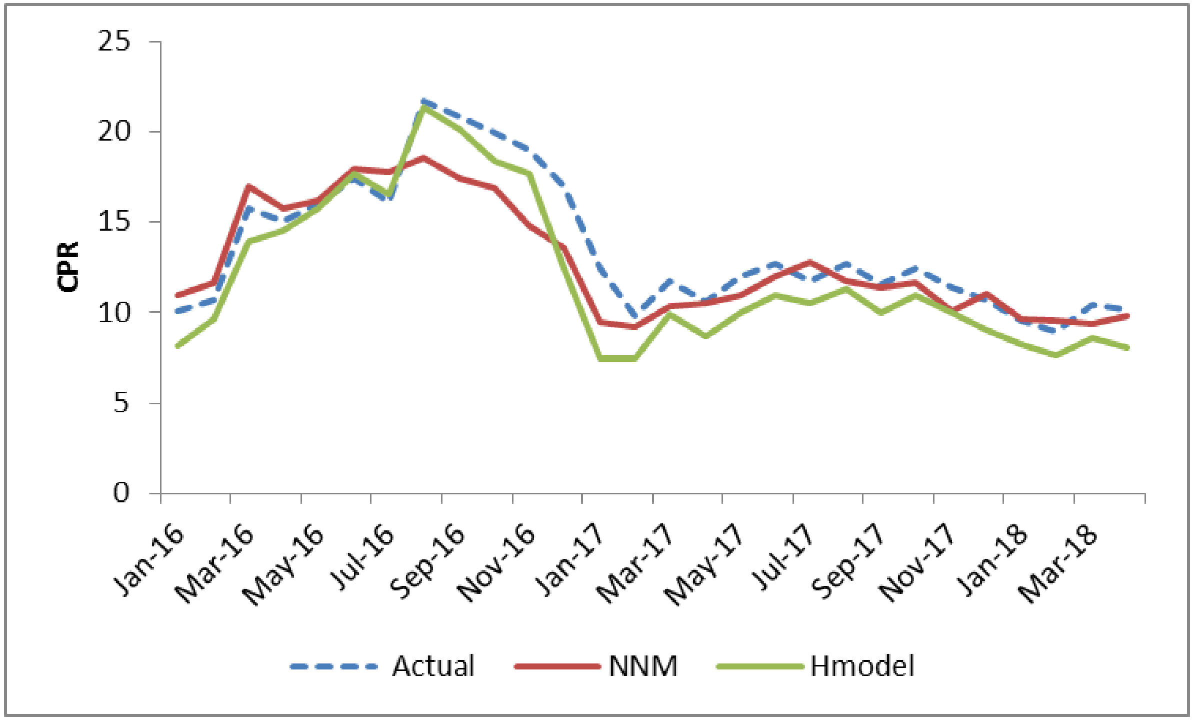
AGENCY 30YR UNIVERSE SPEEDS ERROR TRACKING



- Training Data: 2003 – 2015 Dec. Random sample 10% pools.
- Error tracking is generated using out-of-the-sample pools.

OUT-OF-SAMPLE FORECASTS



- True out-of-time and out-of-sample test.
- Overall fitting is good in out-of-sample test
- Missed the refi wave in second half of 2016

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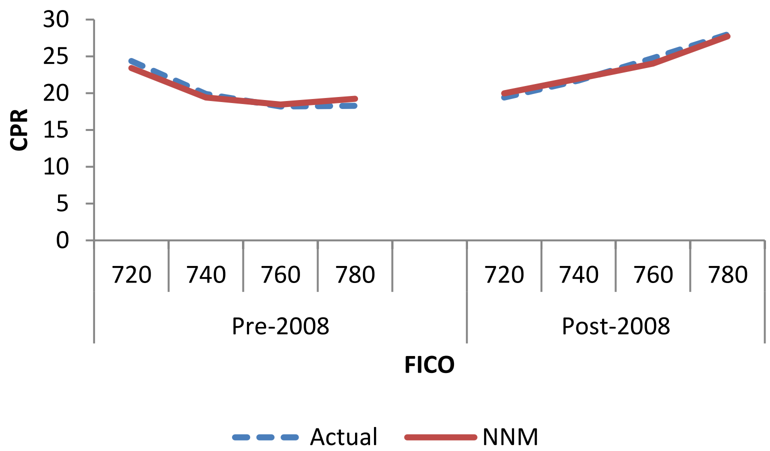
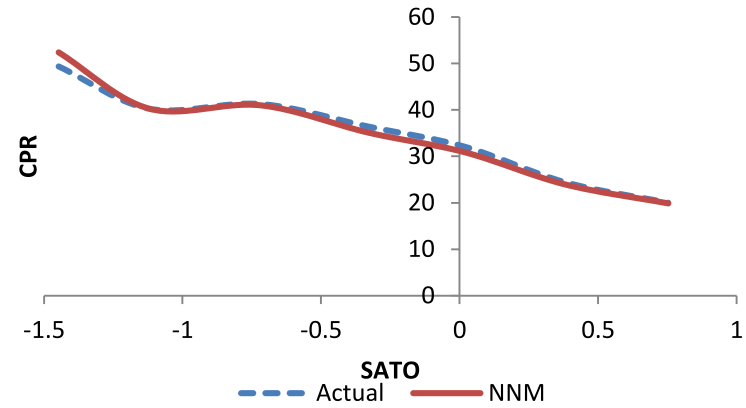
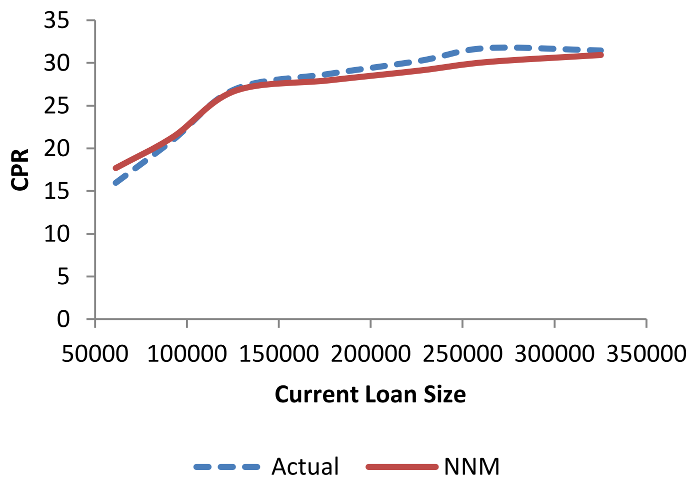
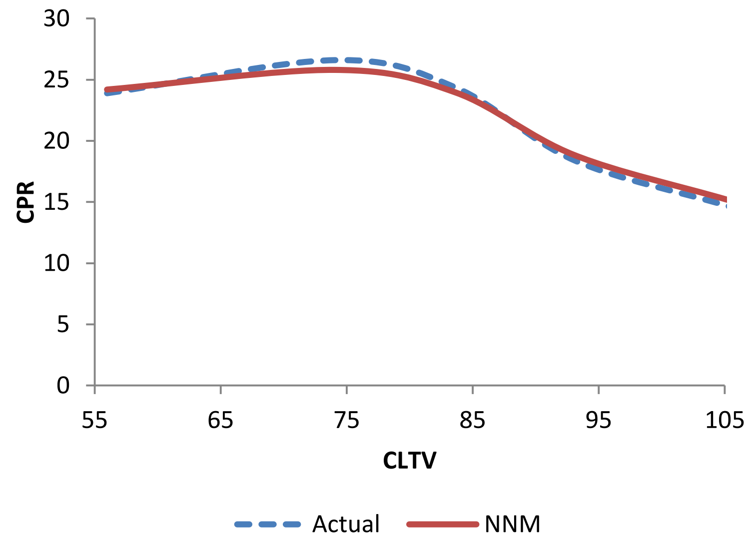
MODEL RISK FACTORS

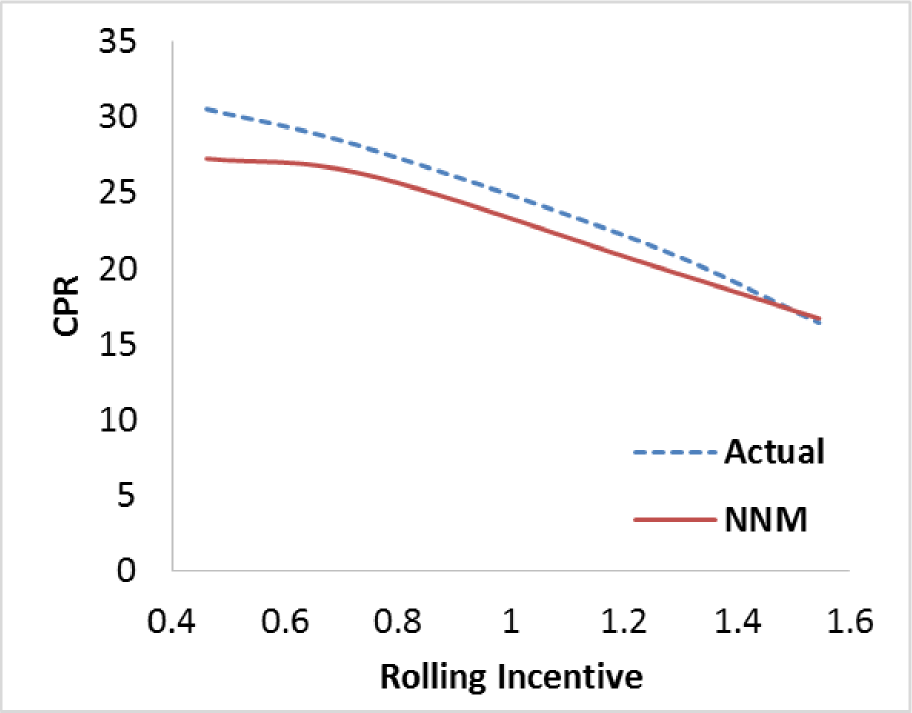








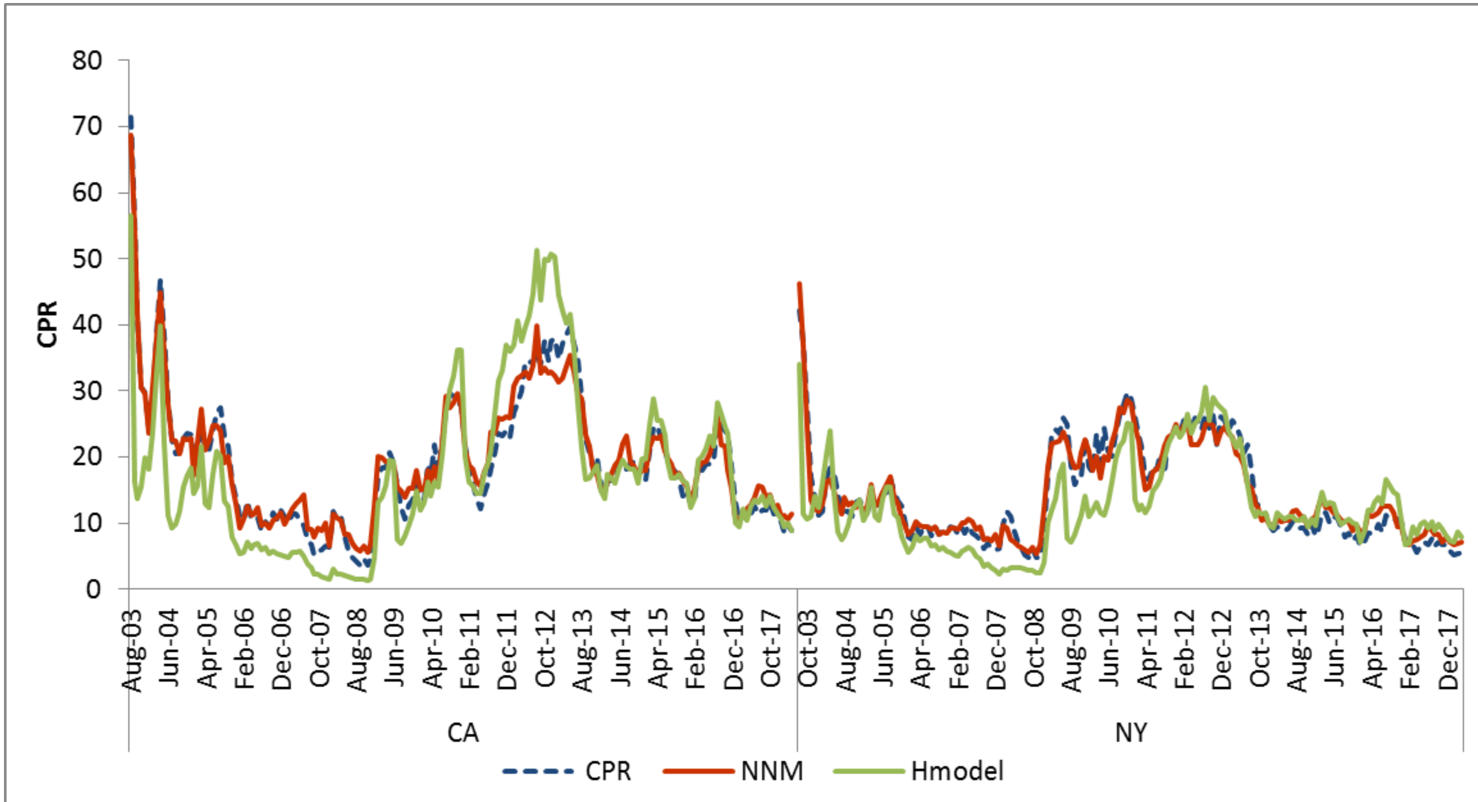
MODEL BURNOUT



NNM and actual prepayment speeds against average incentive in prior 20 months

MODEL POOL VARIABLES VS "HUMAN"MODEL

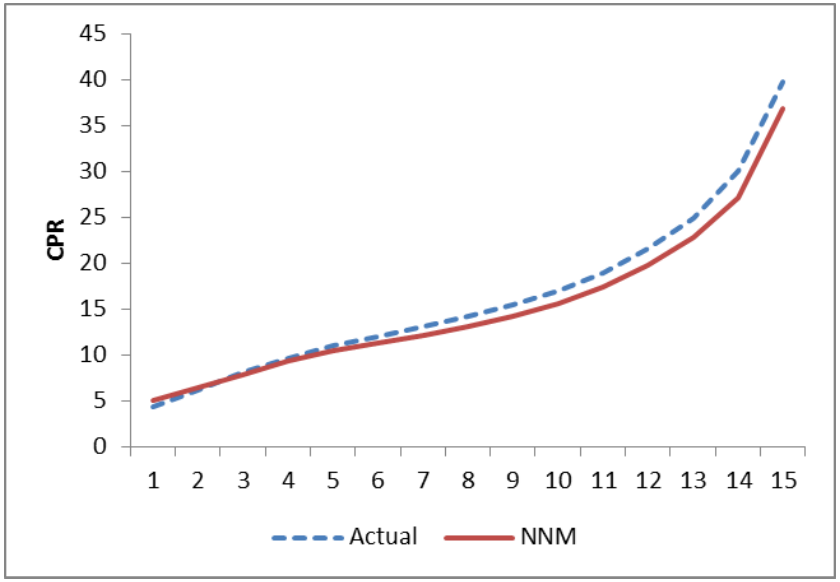
NNM and Hmodel Error Tracking against State Variables

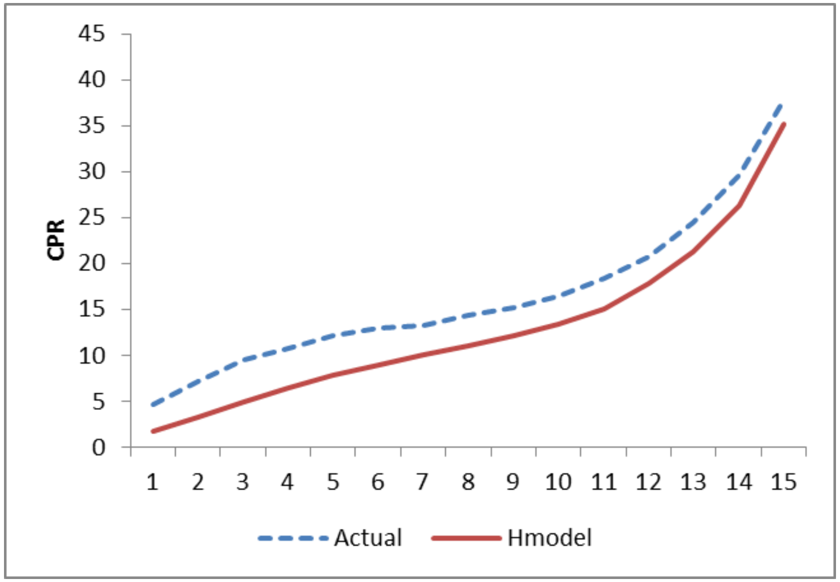


NNM accurately captured state-level prepayment behaviors

MODEL POOL VARIABLES VS HUMAN MODEL

Ranking-Based Sample Error Tracking for Coupon 4s





- Ranking based error tracking methodology provides a comprehensive measure of model accuracy across all pool variables
- NNM performed better than Hmodel

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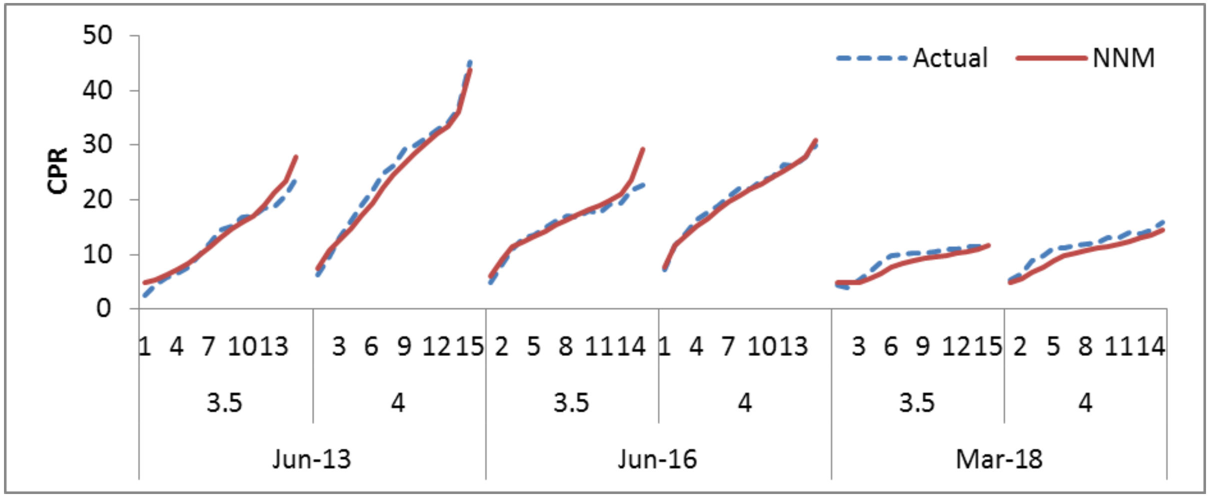
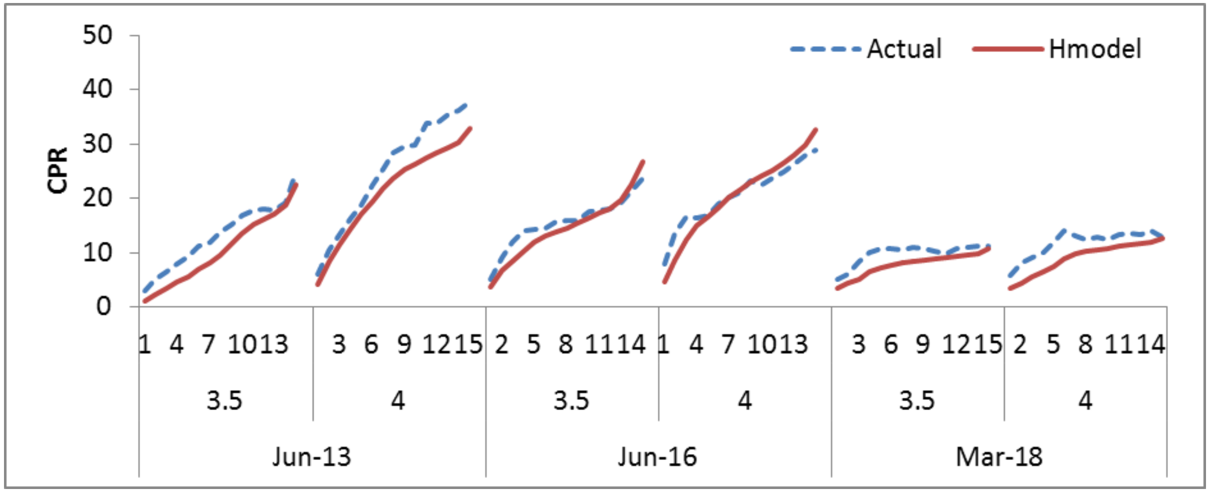
— GENERAL —

MODEL POOL VARIABLES VS HUMAN MODEL





Sample ranking-based error tracking at different time point

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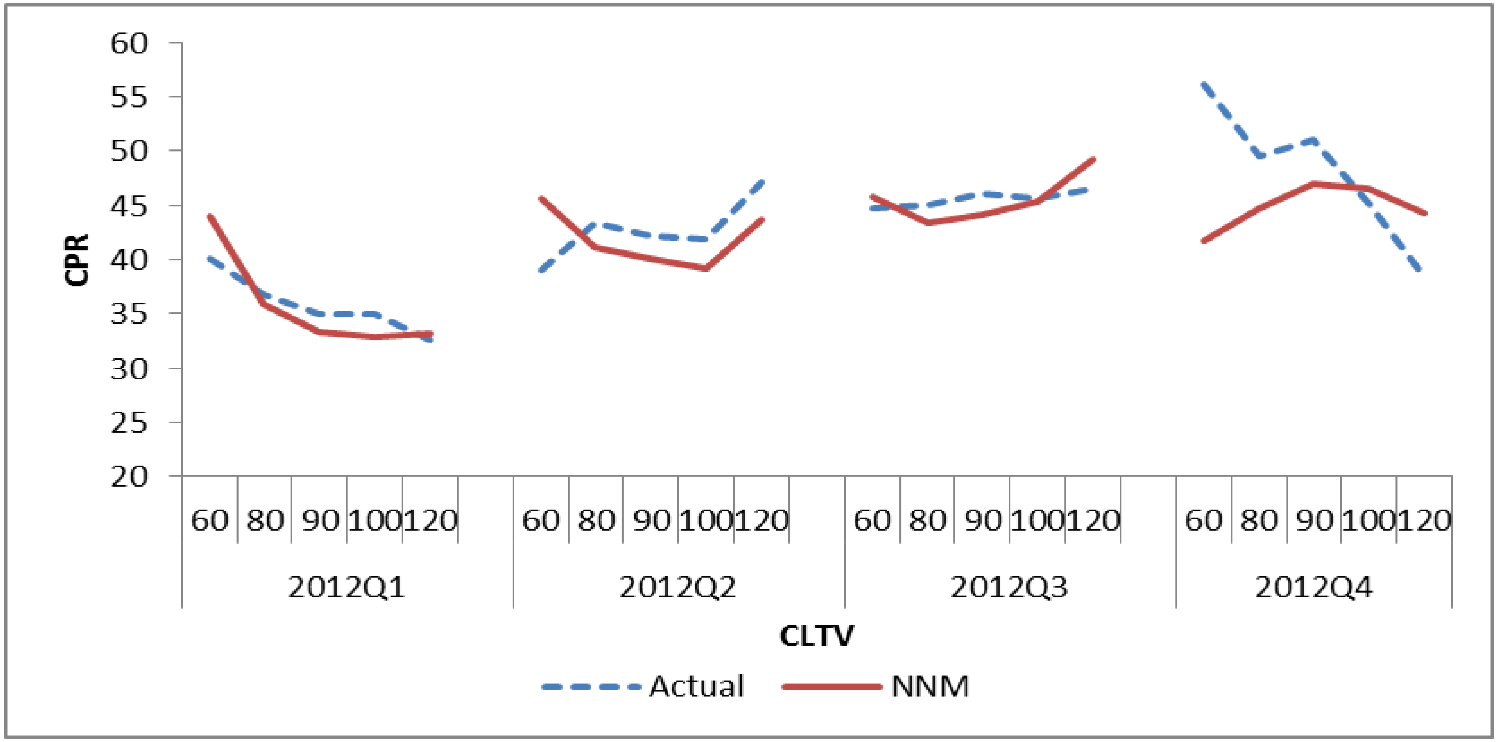
MODEL HARP EFFECTIVENESS

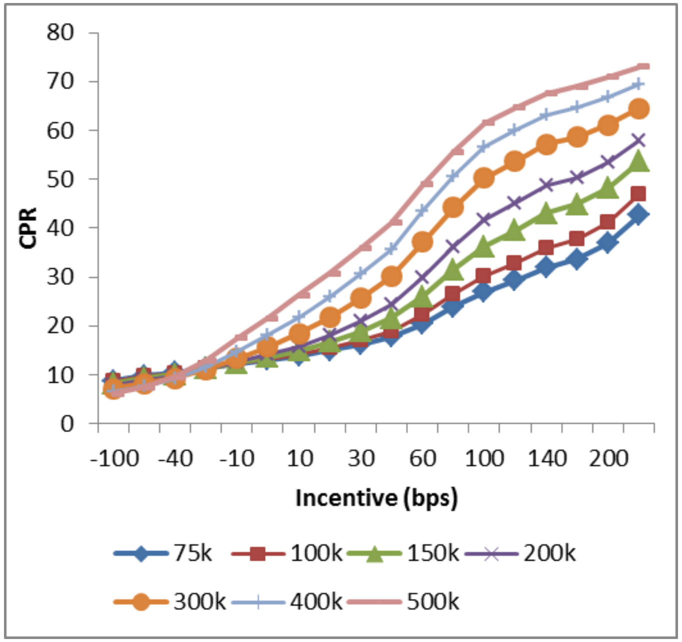
Error Tracking against HARP effectiveness across CLTV Cohorts

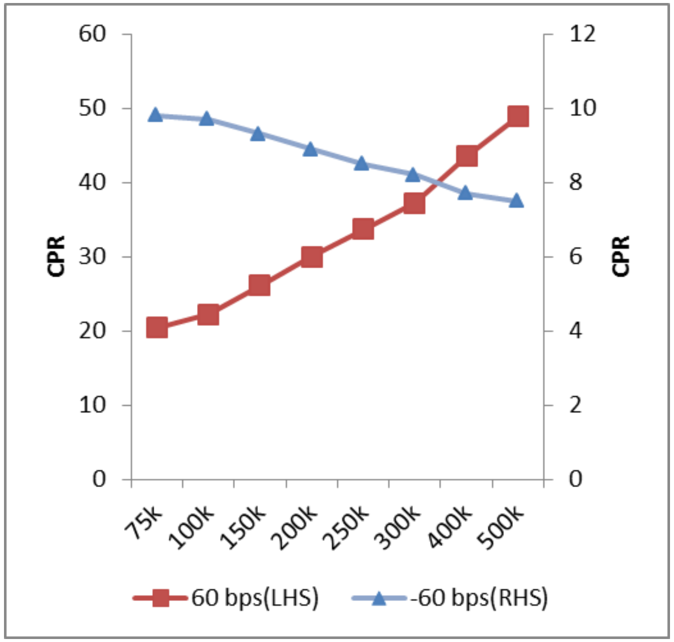


NNM is able to pick up the general trend of HARP effectiveness but missed the complexity of its revolution

MODEL SENSITIVITY

Model prepayment sensitivity to loan sizes and refinance Incentives





NNM captured the prepayment behavior for loan size

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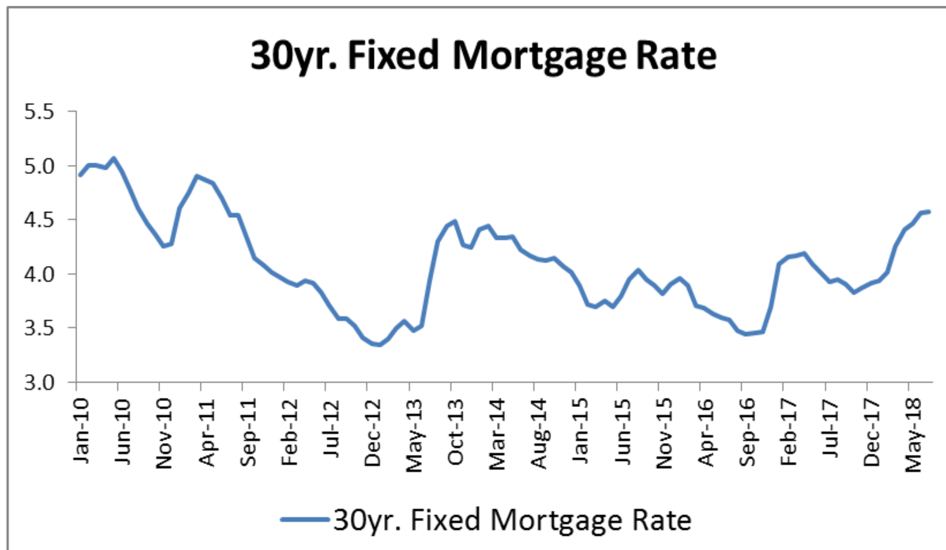
— GENERAL —

"MEDIA EFFECT"

FH 2011 3.5 vs 2010 4 comparisons, across TPO/Retail and Refi/Purchase combinations									
Cohort	Observation Range	CPR	WALA	SATO	CLTV	CLNSZ	Incentive	FICO	Avg.UPB(bn)
		Purchase/Retail							
FH 3.5 2011	Jul.12 - Dec. 12	16.1	13	-5	77	212258	52	770	2.91
FH 4 2010	Nov. 11 - Feb. 12	13.9	15	3	78	201901	45	767	6.26
		Purchase/TPO							
FH 3.5 2011	Jul.2012 - Dec. 12	21.9	12	-3	76	235847	50	770	4.04
FH 4 2010	Nov. 11 - Feb. 12	16.4	16	3	78	224734	45	765	8.66
		Refi/Retail							
FH 3.5 2011	Jul.12 - Dec. 12	29.2	12	-2	66	216270	54	771	7.31
FH 4 2010	Nov. 11 - Feb. 12	15.3	15	11	70	208962	52	766	30.89
		Refi/TPO							
FH 3.5 2011	Jul.12 - Dec. 12	46.1	12	-8	64	269298	46	773	9.58
FH 4 2010	Nov. 11 - Feb. 12	26.2	15	2	69	245496	44	767	23.02

2011 3.5s and 2010 4s prepayment speeds are compared across loan attributes, loan purpose and origination channel

3.5s is much faster than 4s given similar loan attributes and incentive



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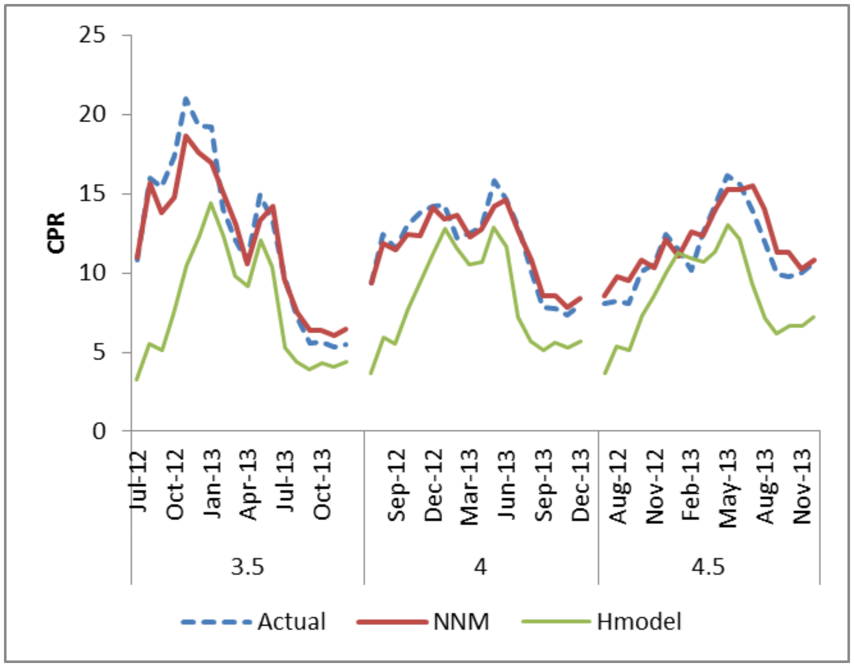
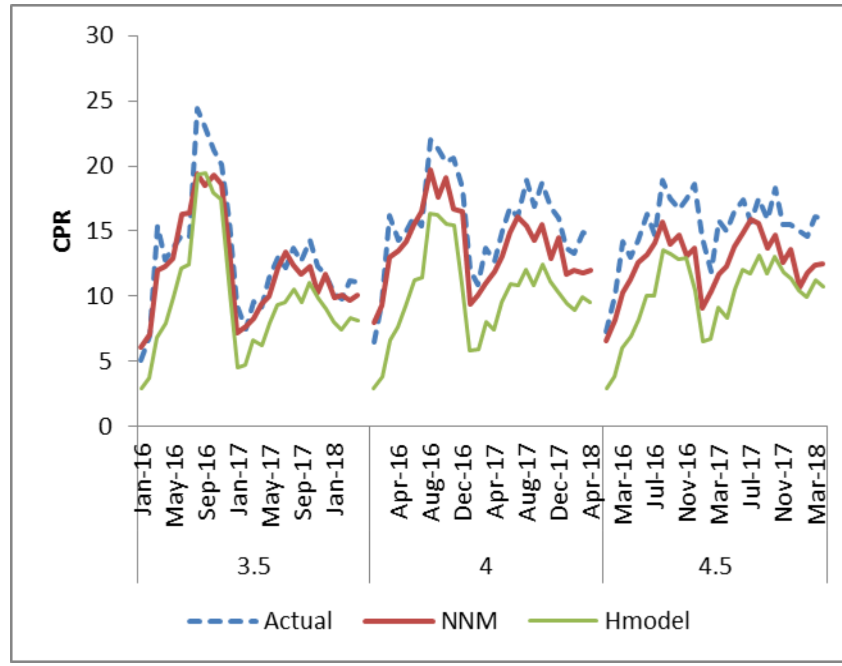
MODEL "MEDIA EFFECT"

2012 Vintage in 2012 refinance wave

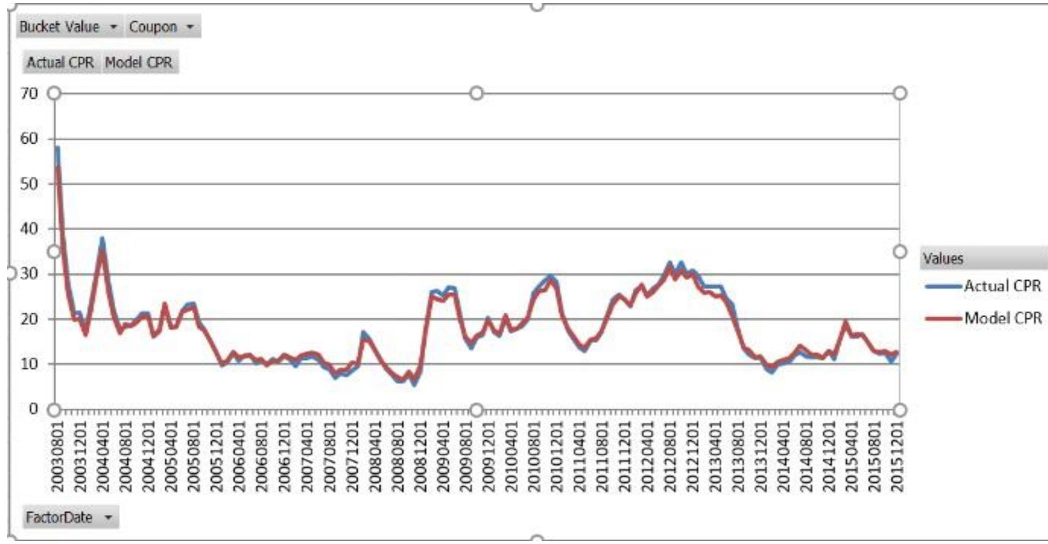


2015 Vintage in 2016 refinance wave



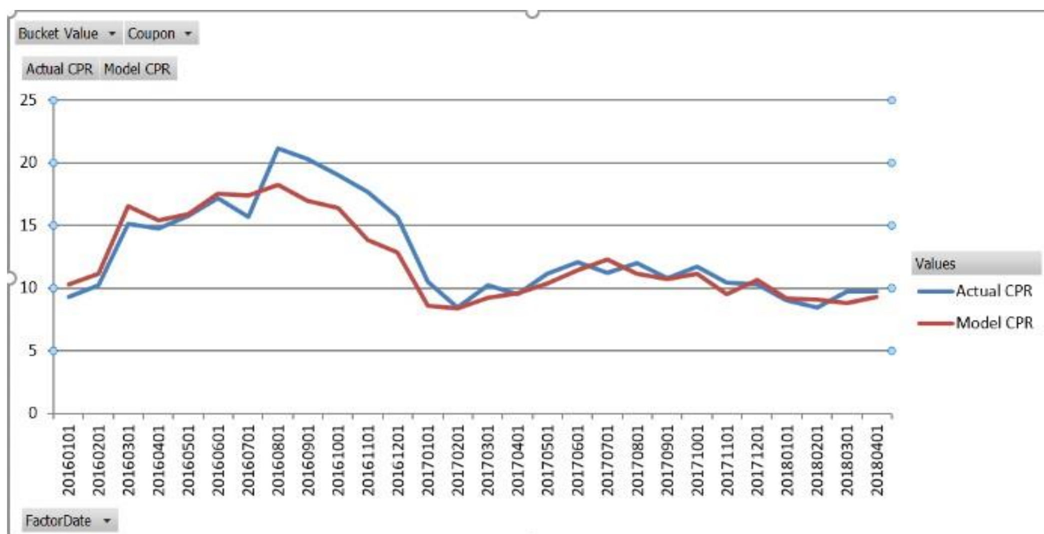
MODEL ERROR TRACKING

In-time
Out-of-sample
(1/2003-12/2015)



1. All attributes statistics are very close on July and August 2016 except CPR.
2. Risk driver is missing, i.e., media effect or regime change

Out-of-time
Out-of-sample
(1/2016-4/2018)



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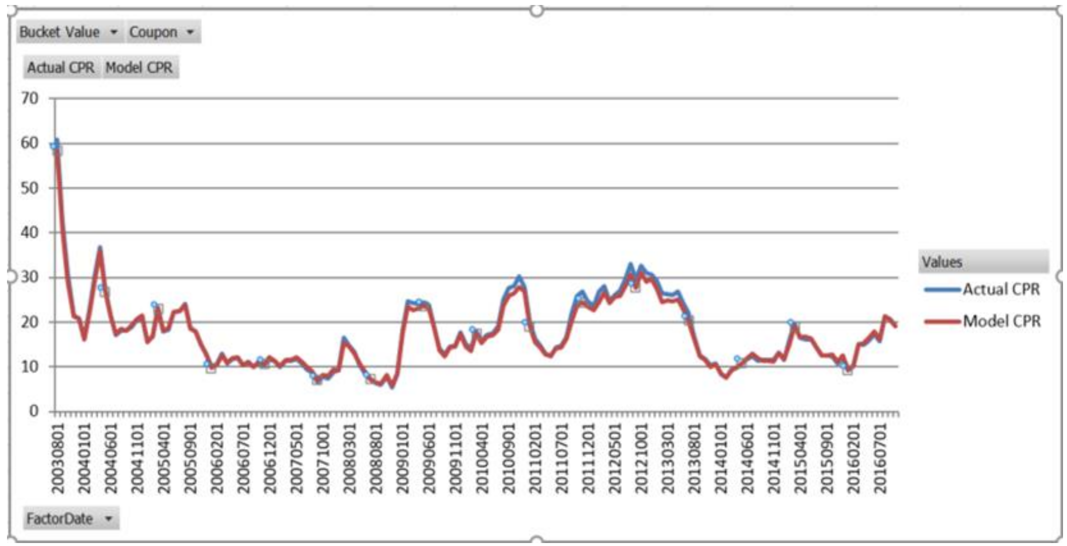
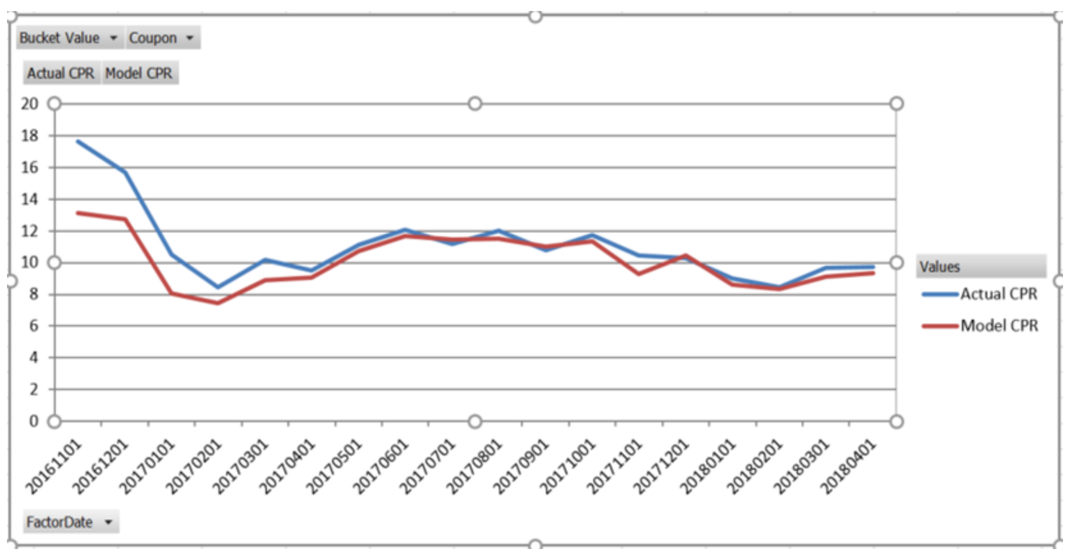
— GENERAL —

MODEL ERROR TRACKING

In-time
Out-of-sample
(1/2003-10/2016)

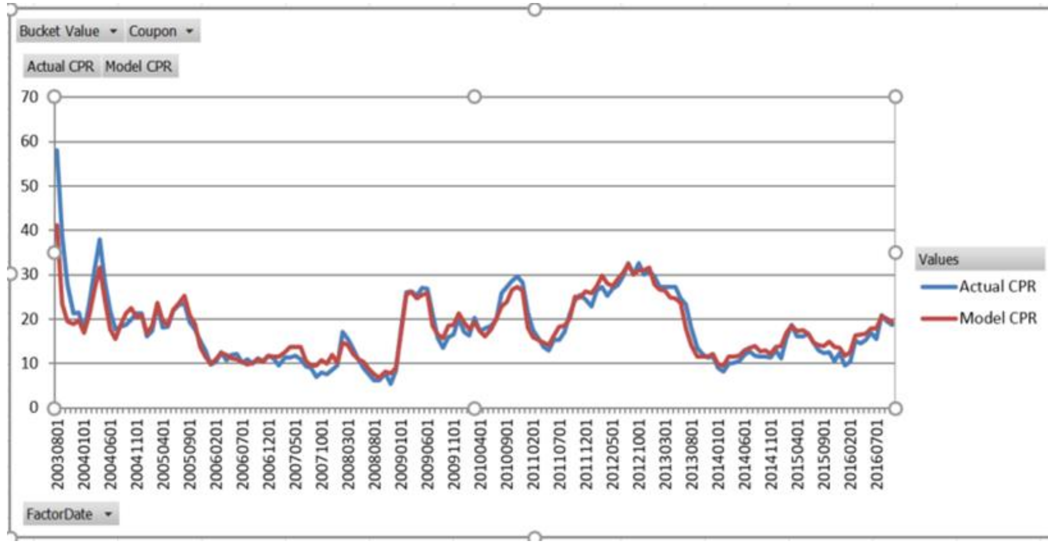


Out-of-time
Out-of-sample
(11/2016-4/2018)



MODEL ERROR TRACKING

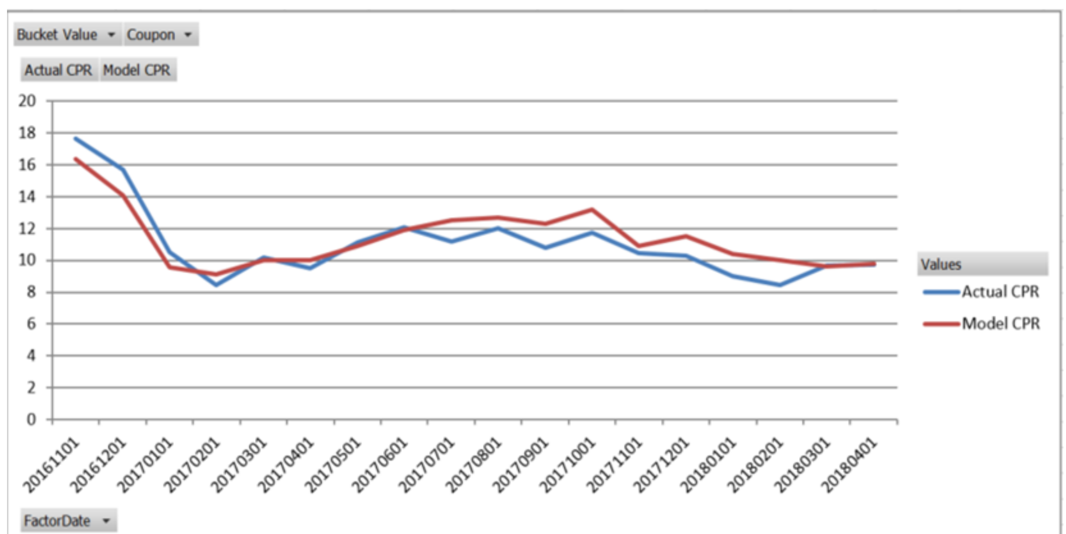
In-time
Out-of-sample
(1/2003-10/2016)



When Increase weights on 8/2016 – 10/2016 by 40 times in training:

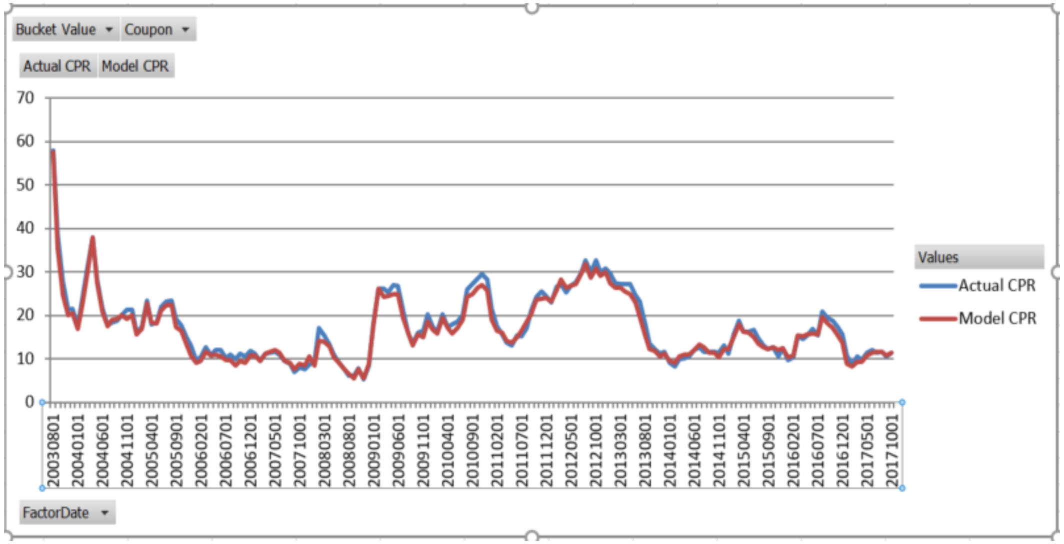
1. Better in the early stage of out-of-time test
2. Sacrifice other period.

Out-of-time
Out-of-sample
(11/2016-4/2018)

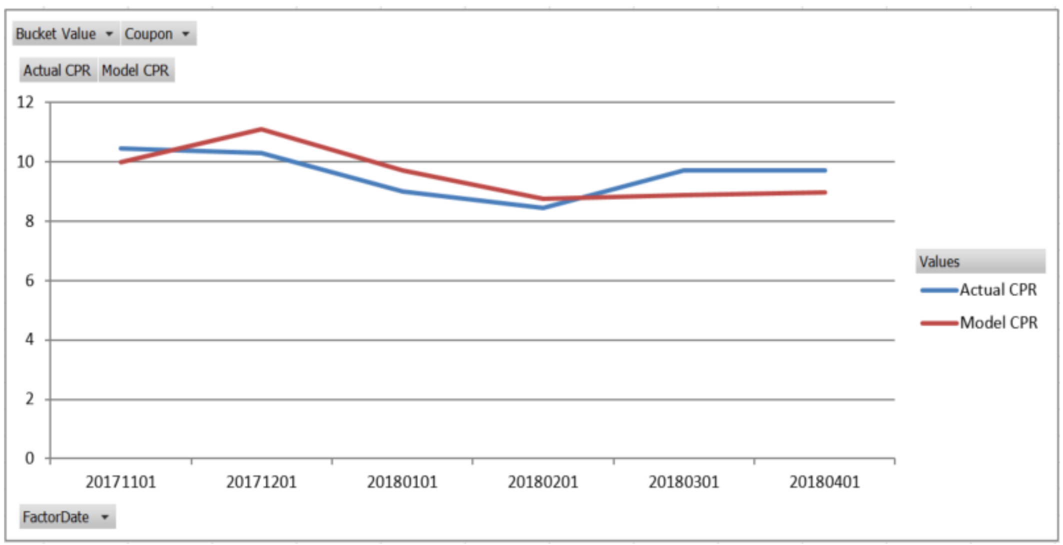


MODEL ERROR TRACKING

In-time
Out-of-sample
(1/2003-10/2017)



Out-of-time
Out-of-sample
(10/2017-4/2018)



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