

Validating and Understanding a Highly Nonlinear Machine Learning Model

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Agenda



1. Prologue *Winning the Indy 500*
2. Modeling Approaches and Validation Principles
3. Why this approach will work
4. Implementation
5. Looking at Outliers
6. Combining Both Approaches
7. Model makes a million dollar difference
8. Conclusion

1

Prologue: Winning the Indy 500

Winning in Indy

Requires both carburetion
and the right non-linear
surface



Winning the Indy 500

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Ever since the automobile was invented, people have been racing.

- » Different types of tracks
- » Different conditions

A mix of air and fuel is injected into the engine; optimizing mixture is key.

In 2018, Will Power and Team Penske had a winning time of just under 3 hours, less than 3 seconds ahead of the second place finisher.

Design innovations can be the difference between winning and losing, but such innovations require extensive testing prior to race day.

Bankers have always rated their borrowers

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A bank that only lends to the safest borrowers will not have much Pre-Provision Net Revenue (PPNR).

A bank that lends to everyone may find that **provisions** exceed PPNR.

Being competitive requires differentiating between the good and the bad borrowers.

A modeling innovation may make a difference, but it must be carefully tested before “race time.”

2

Modeling Approaches

Modeling approaches

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Let data speak

Impose some
structure on data

More structure
imposed on data

Unsupervised Learning

Natural Language Processing

Kernel Methods

Deep Neural Networks

Generalized Additive
Models

Support Vector Machines

Nearest Neighbor

Random Forests

Boosting

Traditional
Nonlinear
Model

New Highly
Nonlinear
Model

Option pricing theory

Hierarchical Bayesian models

Bias correction methods

Structural Equation Modeling

Structural Estimation

Core validation principals

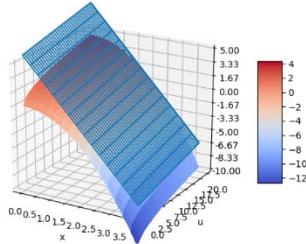


- » Evaluation of conceptual soundness
- » Ongoing monitoring
- » Outcome analyses
- » Effective Challenge

Recipe for validating a highly nonlinear PD model

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ML PD Model



By Moody's Analytics

Data Preparation
time: 20 years

Cook time: 20
minutes

A data table with these columns:

- 1) Default flag
- 2) *Traditional non-linear PD*
- 3) *Highly non-linear PD*
- 4) Set of "risk drivers"
- 5) Set of "cut variables"

And hundreds of thousands of observations (rows)

Procedure: Run a Model Comparison Report to:

- 1) Demonstrate that "highly non-linear model" has better discriminatory power
- 2) Compare the level of the PDs to each other and to actual
- 3) Examine cases where two models produce very different results.
- 4) Look at "higher order effects" and validate "final model"

Recipe for validating a highly nonlinear PD model

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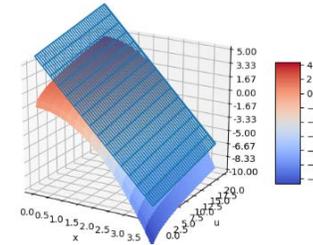
Ingredients

A data table with these columns:

- 1) A default flag
- 2) A PD from a “traditional non-linear model”
- 3) A PD from the “highly non-linear model”
- 4) A set of “risk drivers”
- 5) A set of “cut variables”

And hundreds of thousands of observations

ML PD model



Ingredients

A data table with these columns:

- 1) Default flag
- 2) *Traditional non-linear* PD
- 3) *Highly non-linear* PD
- 4) Set of “risk drivers”
- 5) Set of “cut variables”

And hundreds of thousands of observations (rows)

Method

Procedure: Run a Model Comparison Report to:

- 1) Demonstrate that “highly non-linear model” has better discriminatory power
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By Moody's Analytics

Data Preparation time:
20 years

Cook time: 20 minutes

To garnish

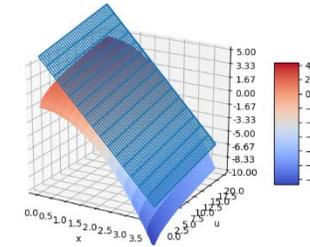
Labels and Formats

Recipe for validating a highly nonlinear PD model

Method: Run a Model Comparison Report to:

- 1) Demonstrate that “highly nonlinear model” has better discriminatory power than the “traditional nonlinear model.”
- 2) Compare the level of the PDs to each other and to actual.
- 3) Examine cases where two models produce very different results.
- 4) Look at “higher order effects” and validate “final model.”

ML PD model



Ingredients

A data table with these columns:

- 1) Default flag
- 2) *Traditional non-linear* PD
- 3) *Highly non-linear* PD
- 4) Set of “risk drivers”
- 5) Set of “cut variables”

And hundreds of thousands of observations (rows)

Method

Procedure: Run a Model Comparison Report to:

- 1) Demonstrate that “highly non-linear model” has better discriminatory power
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By Moody’s Analytics

Data Preparation time:
20 years

Cook time: 20 minutes

To garnish

Labels and Formats

3

Why this Approach Works

Why this approach works

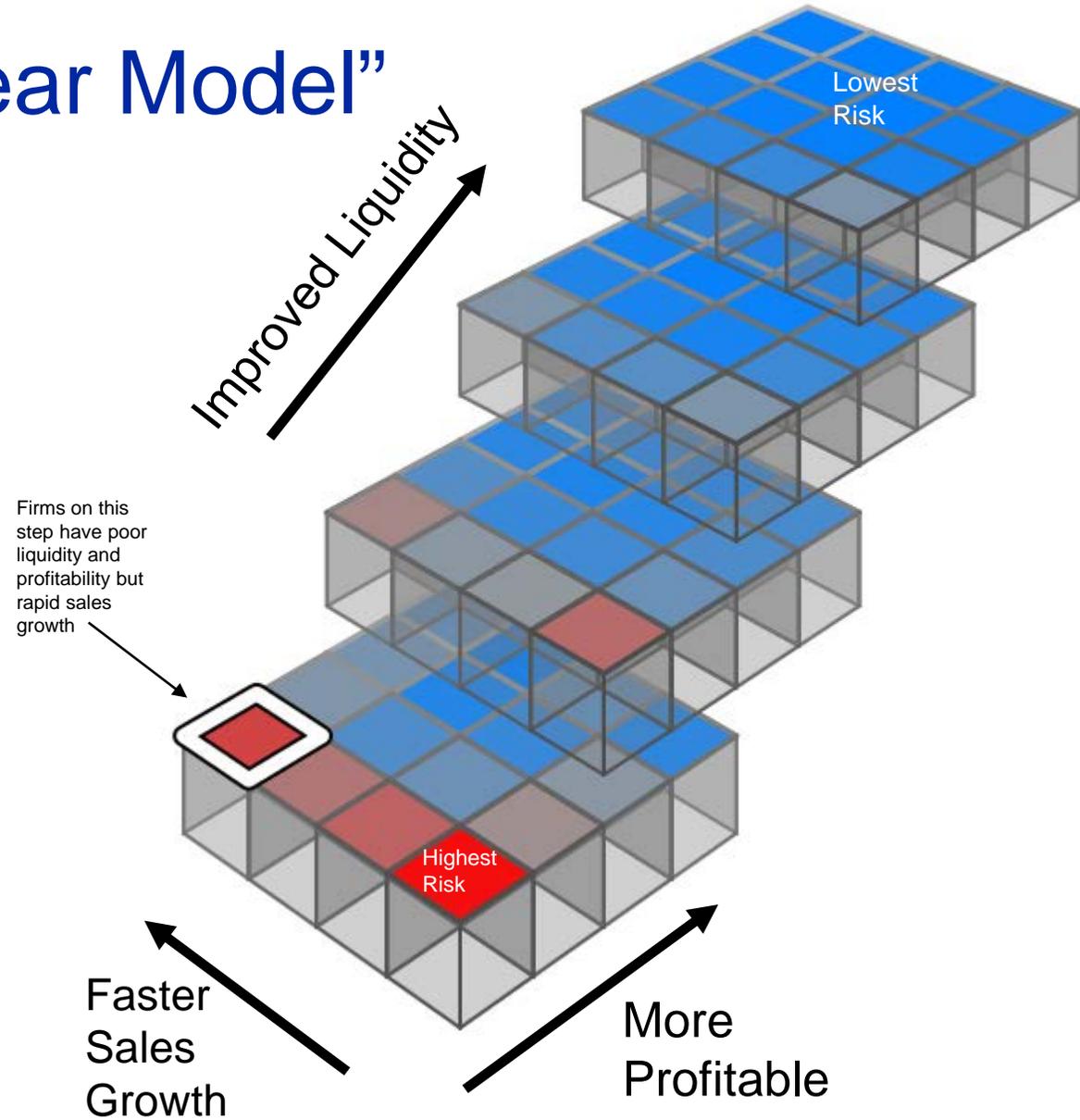


- » We have an objective and concrete outcome variable -- Default
- » Well-established set of risk drivers
- » Large “panel” dataset
- » “Credit Cycle” is treated separately

A “Traditional Nonlinear Model”

Graphic displays interrelationship between three key risk drivers and the RiskCalc EDF as a staircase.

Upstairs is better liquidity, backward is better profit, and leftward is more sales growth. Red steps represent highest risk. Highest risk is where both liquidity and profitability and sales growth are in the lowest quartile, but low profit, low liquidity and rapid sales growth is risky as well.



Highly nonlinear models: decision tree-based ensemble learners

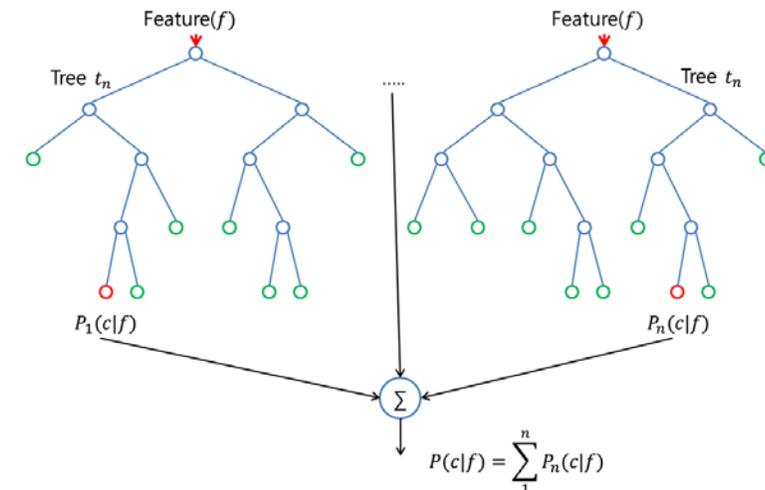
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Random Forest:

- Bootstrap aggregation of classification trees, where each tree casts a unit vote for the most popular class.
- Select n_{tree} , the number of trees to grow, and m_{try} , number of variables.
- For $i = 1$ to n_{tree} : Draw a bootstrap sample from the data. Grow a "random" tree, where, at each node, the best split is chosen from among m_{try} randomly selected variables.
- Prediction of test data is done by majority vote from predictions from the ensemble of trees or by averaging the predictions from individual trees.

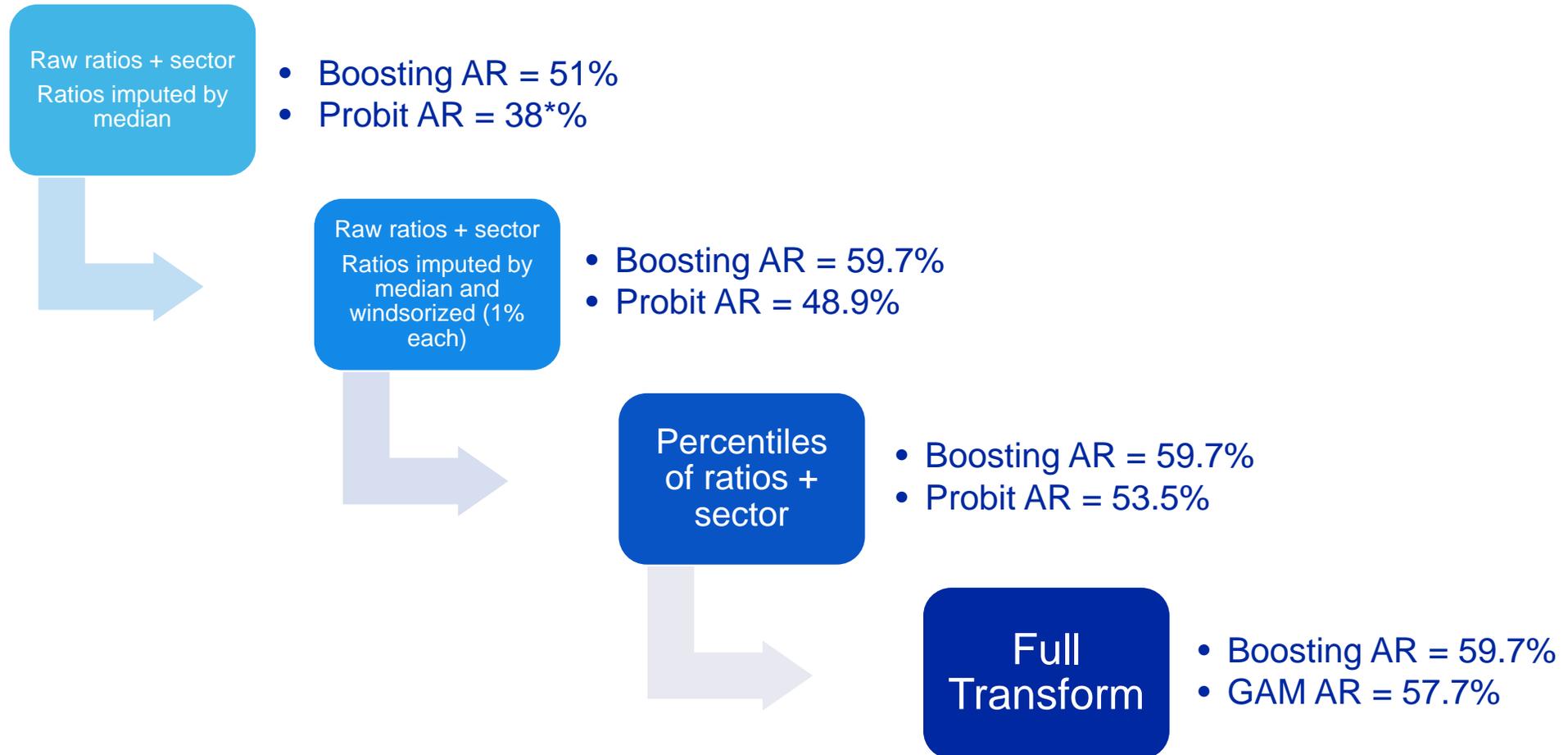
Boosting:

- The classification trees here are trained in a sequence. Each subsequent tree focuses on those cases incorrectly classified in the last round by giving more weight to those cases while constructing the next tree.
- Combine the classifiers by taking a weighted average of their outputs.



Machine Learning – without traditional transformation vs. traditional approach

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Issues to watch



A linear model that includes “year-fixed effects” may have fit the development data better than a linear model without year-fixed effects, but not on future data. The same issue may be hidden within an ML model.

ML fits both economic relationships and data imperfections.

Important to cross-validate at the firm level.

4

Validating a Highly Nonlinear Model

Validating a highly nonlinear model

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Start with the U.S. Credit Research Database:

1,234,854 observations of 250,141 firms with 17,288 defaults from 1994-2018

Acquire a “Traditional Nonlinear PD” – we use the RC4.0 FSO model structure re-estimated on this data.

Acquire a “Highly Nonlinear PD” – we use a Boosting Model estimated on the same data.

Risk drivers are the financial ratios and sector dummies used in RC4.0.

Cut variables are: year, size, and sector.

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MODELING
METHODOLOGY

Model Comparison Report

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Abstract

This automated report is intended to provide a standard set of analyses for evaluating one model relative to another. The report could be used to determine the strengths and weaknesses of a model that is in use when compared to a benchmark model. Alternatively, the report could be used if one is considering the implications of updating a model's calibration, changing the variables in a model, or moving to another modeling approach all together. The report requires as inputs a data set with two model scores (i.e., PDs), a default flag, a set of cut variables, and set of drivers. Given the inputs, the report is set up to be produced automatically. The report compares the rank ordering ability of the models (e.g., it calculates Accuracy Ratios (ARs) and plots Cumulative Accuracy Profiles (CAP) plots) as well as the models' calibration across multiple dimensions of the data. The report can identify circumstances in which one model is systematically understating or overstating credit risk.

Operator's statement: 'Comparing GAM (benchmark) Vs Boosting (Alt)'
Report creation time: 2018-09-26 14:01:06



Provides back



		Table 5: Statistics					
		Min	1st Pctile	5th Pctile	95th Pctile	99th Pctile	Max
PD.alt		0.13	0.19	0.24	5.10	11.50	86.00
PD.bench		0.03	0.12	0.17	5.08	10.10	32.90
Defaults		0.00	0.00	0.00	0.00	100.00	100.00

		Table 4: Statistics				
		10th Pctile	25th Pctile	Median	75th Pctile	90th Pctile
PD.alt		96.60	162.00	56.20	120.00	295.00
PD.bench		100.00	166,000.00	81.50	127.00	321.00
	Number	860.00	12,700.00	195.00	314.00	381.00
		100.00	25,500,000.00	1,200.00	900.00	

	Number	Min	1st Pctile	5th Pctile	95th Pctile	99th Pctile	Max
ratio.cash_assets	1,234,854	0.00	0.00	3,860.00	16,100.00	42.90	
ratio.changeinroa	1,234,854	10.10	3,860.00	16,100.00	42.90		
ratio.changeinwecoversales	1,234,854	0.73	7.86	15.40	243,000.00		
ratio.currliabilities_sales	1,234,854	0.10	37.70	69.40			
ratio.ebitda_interestexp	1,234,854	1.44	309.00	1,200.00			
ratio.inventory_sales	1,234,854	0.00	12.30	36.30			
ratio.re_currliabilities	1,234,854	0.00	19.70	103.00			
ratio.roa	1,234,854	0.00	411,000.00	2,360,000.00			
ratio.salesgrowth	1,234,854						
ratio.size	1,234,854						

Summary Statistics



Provides back



		Min	1st Pctile	5th Pctile	95th Pctile	99th Pctile	Max
Table 5: Statistics							
PD.alt		0.13	0.19	0.24	5.10	11.50	86.00
PD.bench		0.03	0.12	0.17	5.08	10.10	32.90
Defaults		0.00	0.00	0.00	0.00	100.00	100.00
Table 4: Statistics							
		10th Pctile	25th Pctile	Median	75th Pctile	90th Pctile	
PD.alt	Number	81.10	90.90	96.60	120.00	166.000.00	
PD.bench		56.20	57.80	56.20	57.80	57.80	
		295.00	578.00	100.00	166.000.00	81.50	127.00
PD.alt		321.00	549.00	860.00	12,700.00	195.00	314.00
PD.bench		381.00	1,200.00	900.00	25,500,000.00		
Defaults							
PD_pctdiff							
ratio.cash_assets							
ratio.changeinroa							
ratio.changeinweversales							
ratio.currliabilities_sales							
ratio.ebitda_interestexp	1,234,854	10.10	3,860.00	16,100.00	42.90		
ratio.inventory_sales	1,234,854	0.73	7.86	15.40	243,000.00		
ratio.ltdbt_ltdbtandnetworth	1,234,854	0.10	37.70	69.40			
ratio.re_currliabilities	1,234,854	1.44	309.00	1,200.00			
ratio.roa	1,234,854	0.00	12.30	36.30			
ratio.salesgrowth	1,234,854	0.00	19.70	103.00			
ratio.size	1,234,854	0.00	411,000.00	2,360,000.00			

Summary Statistics

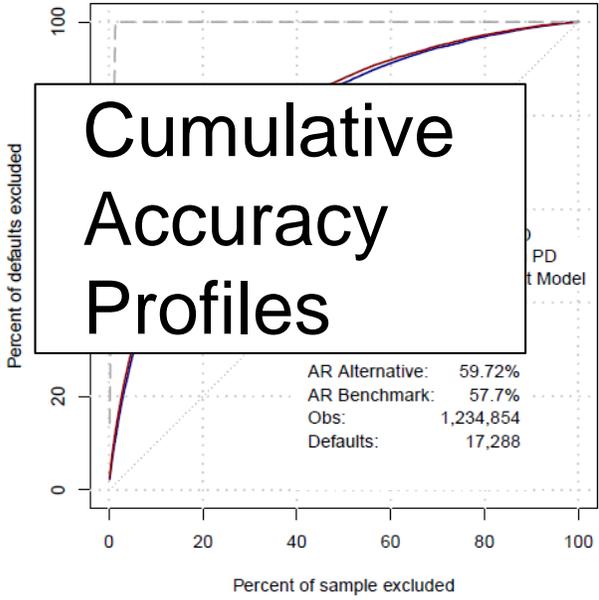


Figure 2: Cap Plot



Provides back



	Min	1st Pctile	5th Pctile	95th Pctile	99th Pctile	Max
PD.alt	0.13	0.19	0.24	5.10	11.50	86.00
PD.bench	0.03	0.12	0.17	5.08	10.10	32.90
Defaults	0.00	0.00	0.00	0.00	100.00	100.00

	10th Pctile	25th Pctile	Median	75th Pctile	90th Pctile
PD.alt	81.10	96.60	120.00	162.00	255.00
PD.bench	56.20	66.20	100.00	166.00	295.00

	Number
PD.alt	1
PD.bench	1
Defaults	1
PD.pctdiff	1
ratio.cash_assets	1
ratio.changeinroa	1
ratio.changeinwcoveralsales	1
ratio.currliabilities_sales	1,234,854
ratio.ebitda_interestexp	1,234,854
ratio.inventory_sales	1,234,854
ratio.ltdebt_ltdbtandnetworth	1,234,854
ratio.re_currliabilities	1,234,854
ratio.roa	1,234,854
ratio.salesgrowth	1,234,854
ratio.size	1,234,854

Summary Statistics

Year	Number of Obs.	Number of Defaults	AR Alt. Model	AR Bench. Model	Difference
1994	3,803	28	62.06	52.87	9.19
1995	6,618	51	68.70	49.52	19.18
1996	13,680	50	63.59	53.47	10.12
1997	19,467	60	63.51	57.16	6.35
1998	33,732	209	49.74	47.22	2.53
1999	39,967	482	54.28	51.90	2.38

Category	Number of Obs.	Number of Defaults	AR Alt. Model	AR Bench. Model	Difference
A: <0.5m	77,514	1,511	44.40	43.74	0.66
B: 0.5-1m	53,983	1,167	53.05	52.44	0.61
C: 1-2.5m					
D: 2.5-5m					
E: 5-10m					
F: 10-20m					
Number of Obs.					
Agriculture	27,269				
Business_Products	134,598				
Business_Services	160,678				
Communication	15,930				
Construction	156,904				
Consumer_Products	62,014				
Health_Care	111,315				
HiTech	35,622				
Mining	25,455				
Services	148,209				
Trade	272,277				
Transportation	49,040				
Unassigned	21,184				
Utilities	14,359				
	623	55,07	50.44	47.23	
	325	58.96	52.55	6.41	
	70	63.93	54.98	8.95	

Performance Stats "by Cut"

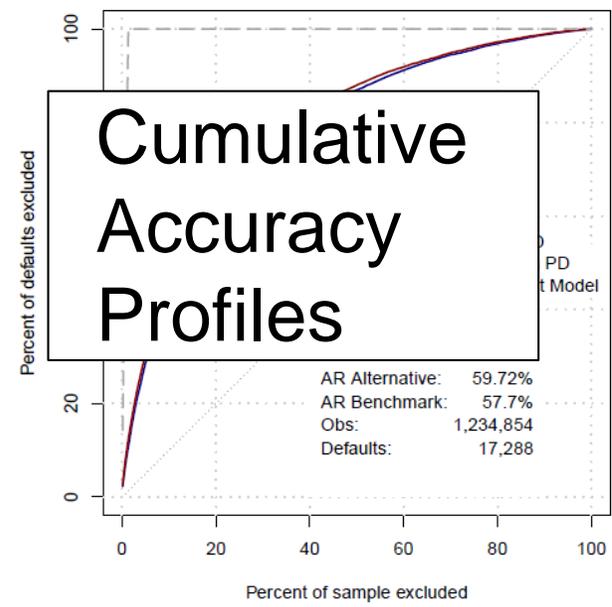
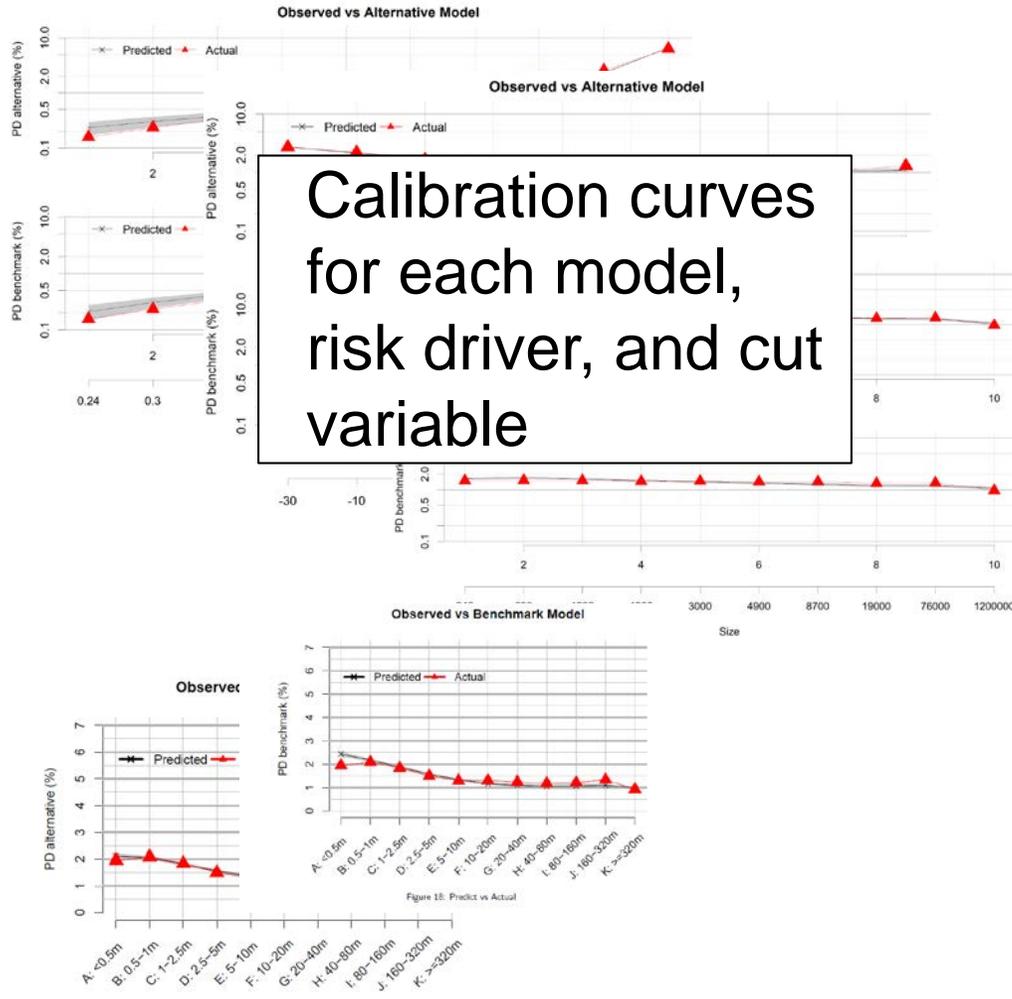


Figure 2: Cap Plot

Provides back



Calibration curves for each model, risk driver, and cut variable

Table 5: Statistics

	Min	1st Pctile	5th Pctile	95th Pctile	99th Pctile	Max
PD.alt	0.13	0.19	0.24	5.10	11.50	86.00
PD.bench	0.03	0.12	0.17	5.08	10.10	32.90
Defaults	0.00	0.00	0.00	0.00	100.00	100.00

Table 4: Statistics

	10th Pctile	25th Pctile	Median	75th Pctile	90th Pctile
PD.alt	0.13	0.19	0.24	5.10	11.50
PD.bench	0.03	0.12	0.17	5.08	10.10

Table 7: stmt_year

Year	Number of Obs.	Number of Defaults	AR Alt. Model	AR Bench. Model	Difference
1994	3,803	28	62.06	52.87	9.19
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1998	33,732	209	49.74	47.22	2.53
1999	39,967	482	54.28	51.90	2.38

Table 8: cat_net_sale_cpi_adj

Category	Number of Obs.	Number of Defaults	AR Alt. Model	AR Bench. Model	Difference
A: <0.5m	77,514	1,511	44.40	43.74	0.66
B: 0.5-1m	53,983	1,167	53.65	52.44	1.21
C: 1-2.5m					
D: 2.5-5m					
E: 5-10m					
F: 10-20m					
G: >20m					

Summary Statistics

Performance Stats "by Cut"

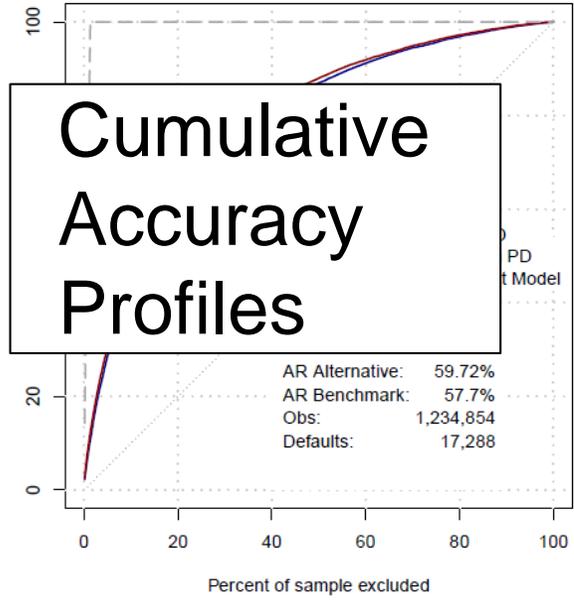


Figure 2: Cap Plot

Provides back

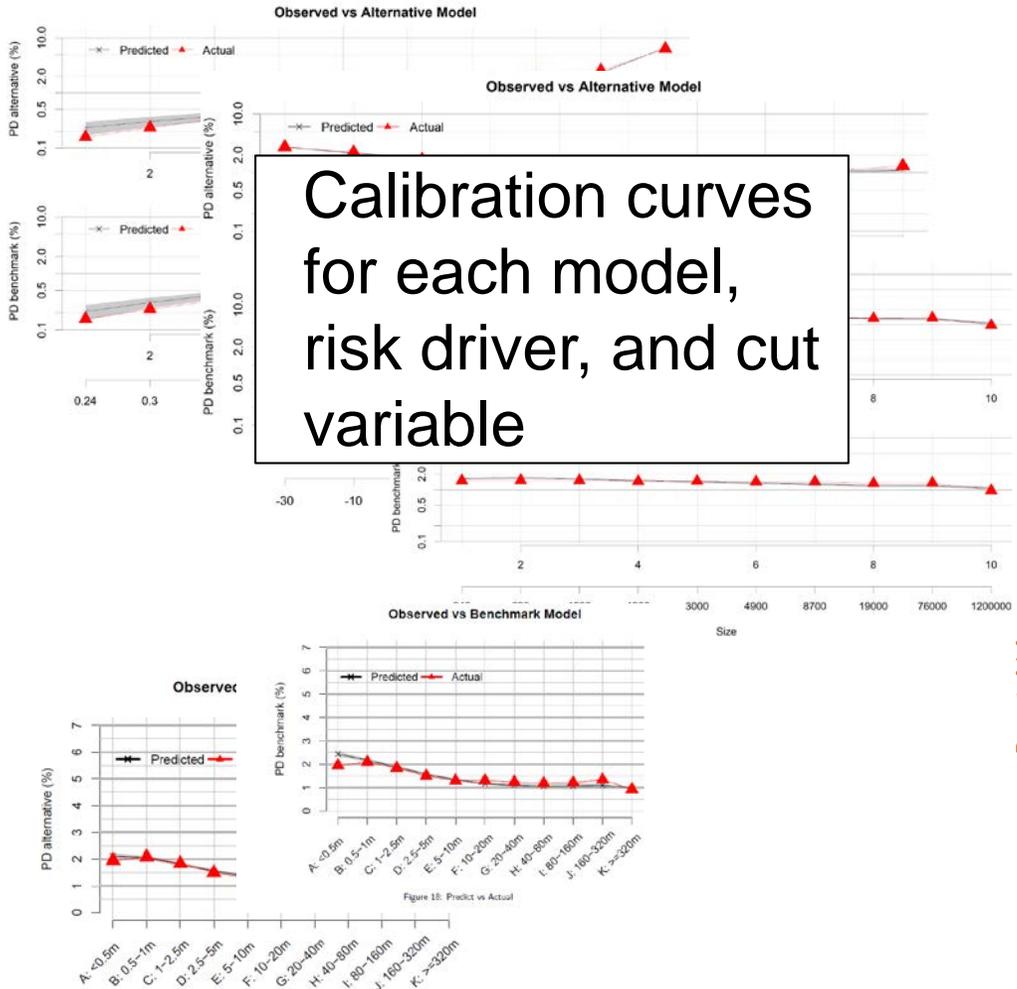


Table 5: Statistics

	Min	1st Pctile	5th Pctile	95th Pctile	99th Pctile	Max
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PD.bench	0.03	0.12	0.17	5.08	10.10	32.90
Defaults	0.00	0.00	0.00	0.00	100.00	100.00

Table 4: Statistics

	10th Pctile	25th Pctile	Median	75th Pctile	90th Pctile
PD.alt	0.13	0.19	0.24	5.10	11.50
PD.bench	0.03	0.12	0.17	5.08	10.10
Defaults	0.00	0.00	0.00	0.00	100.00

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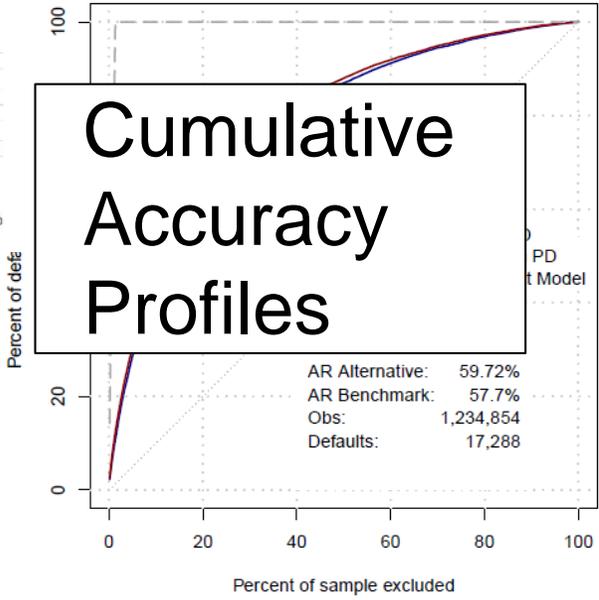
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Category	Number of Obs.	Number of Defaults	AR Alt. Model	AR Bench. Model	Difference
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B: 0.5-1m	53,983	1,167	52.05	50.44	1.61
C: 1-2.5m	156,904	62,014	62.014	62.014	0.00
D: 2.5-5m	111,315	35,622	35.622	35.622	0.00
E: 5-10m	148,209	27,277	27.277	27.277	0.00
F: 10-20m	49,040	21,184	21.184	21.184	0.00
G: >=20m	14,359	14,359	14.359	14.359	0.00

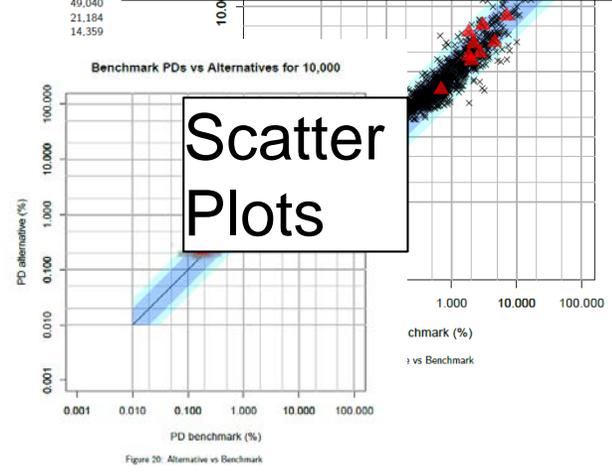
Summary Statistics

Performance Stats "by Cut"

Cumulative Accuracy Profiles



Scatter Plots



Findings

Boosting model delivers better CAP plot

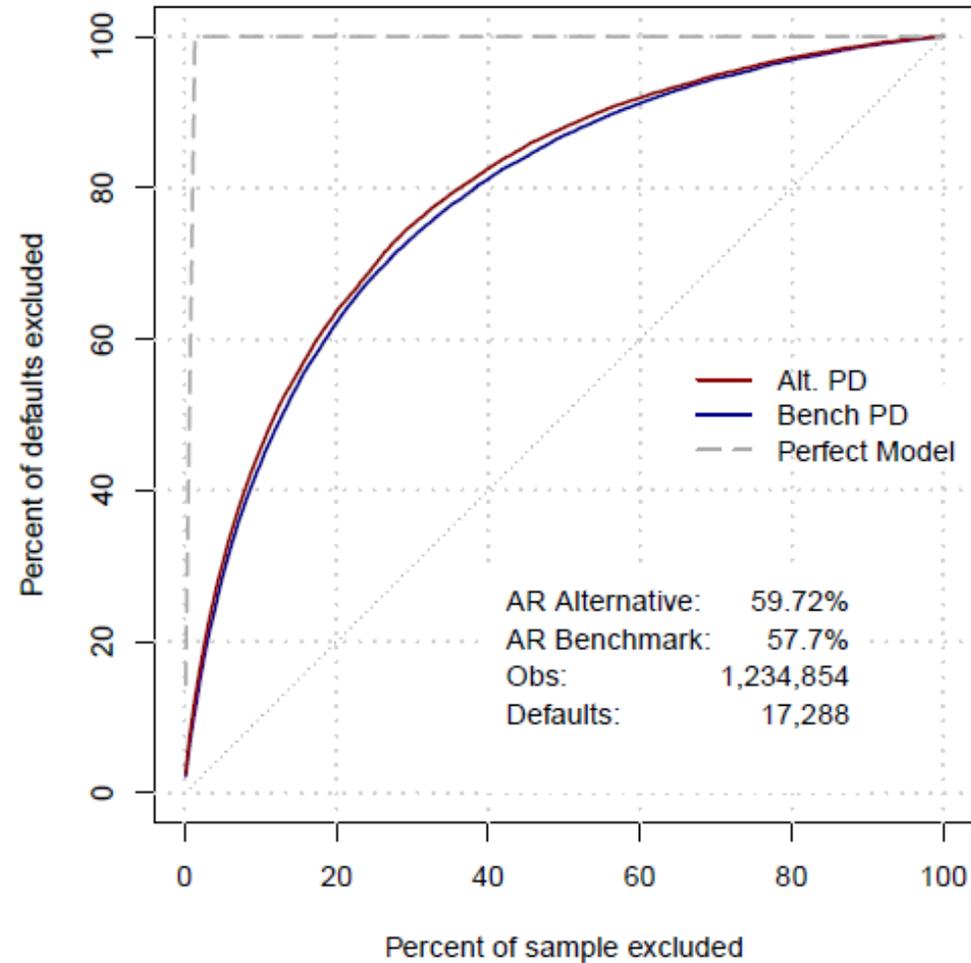


Figure 2: Cap Plot

Performance differences are robust across cuts

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Groupings Based on Sector

	Number of Obs.	Number of Defaults	AR Alt. Model	AR Bench. Model	Difference
Business Products	134,598	1,977	59.70	59.07	0.64
Business Services	160,678	1,891	55.45	53.39	2.05
Consumer Products	62,014	1,011	60.34	59.10	1.24
Health Care	111,315	918	52.28	48.25	4.03
Agriculture	27,269	443	50.59	48.83	1.75
Communication	15,930	269	55.12	51.72	3.40
Construction	156,904	3,416	62.62	60.45	2.17
HiTech	35,620	398	63.08	60.37	2.72
Mining	25,455	549	60.22	54.63	5.58
Services	148,209	1,900	57.79	55.77	2.02
Trade	272,276	3,498	58.85	57.39	1.46
Transportation	49,040	623	53.67	50.44	3.23
Unassigned	21,184	325	58.96	52.55	6.41
Utilities	14,359	70	63.93	54.98	8.95

Performance differences are robust across cuts



Groupings Based on Financial Statement Year

	Number of Obs.	Number of Defaults	AR Alt. Model	AR Bench. Model	Difference
1994	3,803	28	62.06	52.87	9.19
1995	6,618	51	68.70	49.52	19.18
1996	13,680	50	63.59	53.47	10.12
1997	19,467	60	63.51	57.16	6.35
1998	33,732	209	49.74	47.22	2.53
1999	39,967	482	54.28	51.90	2.38
2000	44,935	505	58.43	55.34	3.09
2001	48,977	599	55.94	53.41	2.54
2002	54,152	561	63.09	60.66	2.43
2003	62,600	610	59.64	59.50	0.14
2004	68,518	685	55.55	54.53	1.02
2005	72,504	666	56.52	54.35	2.17
2006	72,680	1,146	60.54	58.22	2.32
2007	75,224	2,064	60.74	59.50	1.25
2008	77,579	2,528	54.48	53.55	0.92
2009	76,396	1,808	56.40	55.04	1.36
2010	75,136	1,285	58.89	56.12	2.77
2011	72,417	927	59.70	58.05	1.65
2012	63,746	610	61.11	59.41	1.70
2013	70,488	637	63.47	59.62	3.85
2014	67,027	722	64.77	61.41	3.36
2015	59,662	734	65.73	63.44	2.29
2016	47,066	309	66.36	63.37	2.99
2017	8,477	12	67.62	55.45	12.17

Performance differences are robust across cuts

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Groupings Based on Firm Size (Total Assets)

	Number of Obs.	Number of Defaults	AR Alt. Model	AR Bench. Model	Difference
<500k	77,514	1,511	44.40	43.74	0.66
500k to 1MM	53,092	1,107	53.95	52.44	1.51
1MM to 2.5MM	133,801	2,462	54.95	53.78	1.16
2.5MM to 5MM	153,407	2,300	59.48	57.89	1.59
5MM to 10MM	180,521	2,342	61.08	59.05	2.03
10MM to 20MM	172,033	2,247	59.85	58.55	1.31
20MM to 40MM	131,143	1,629	59.20	56.96	2.24
40MM to 80MM	92,164	1,090	61.72	59.23	2.49
80MM to 160MM	64,154	779	61.49	59.59	1.91
160MM to 320MM	43,923	587	60.37	59.19	1.18
>320MM	133,099	1,234	65.98	62.48	3.49

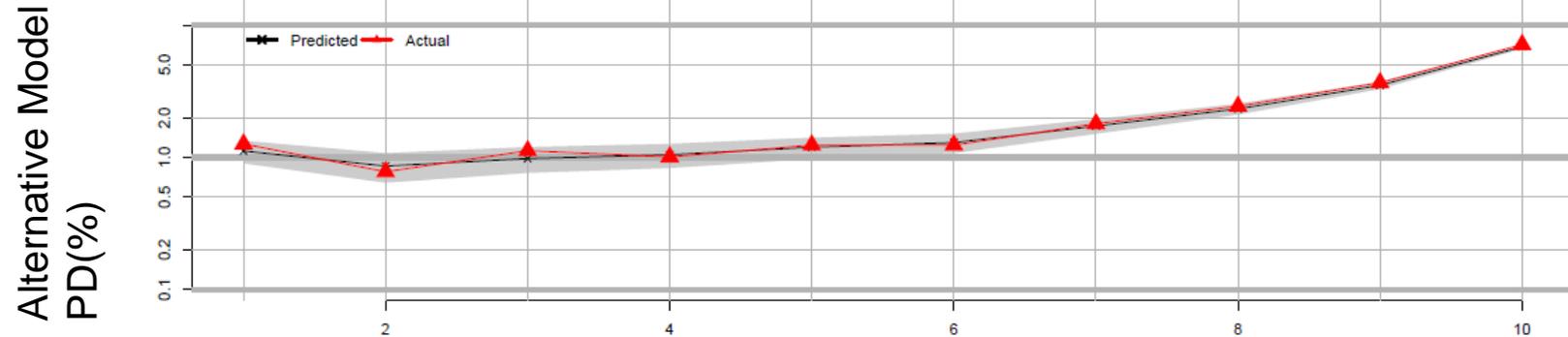
Highly nonlinear model fits industry differences better



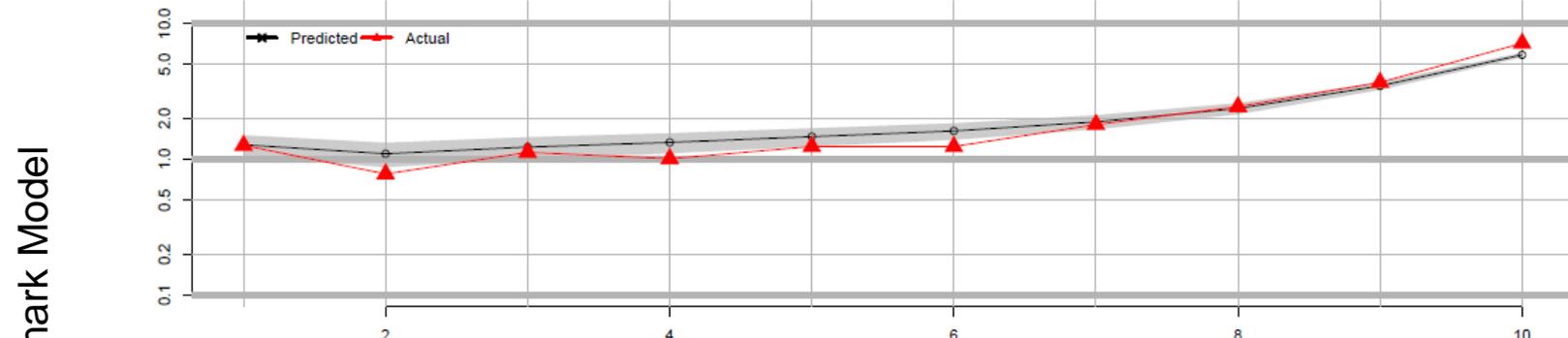
Traditional
Nonlinear Model
underweights
Current
Liabilities to
Sales in
Construction

Construction Only

Observed vs Alternative Model



Observed vs Benchmark Model



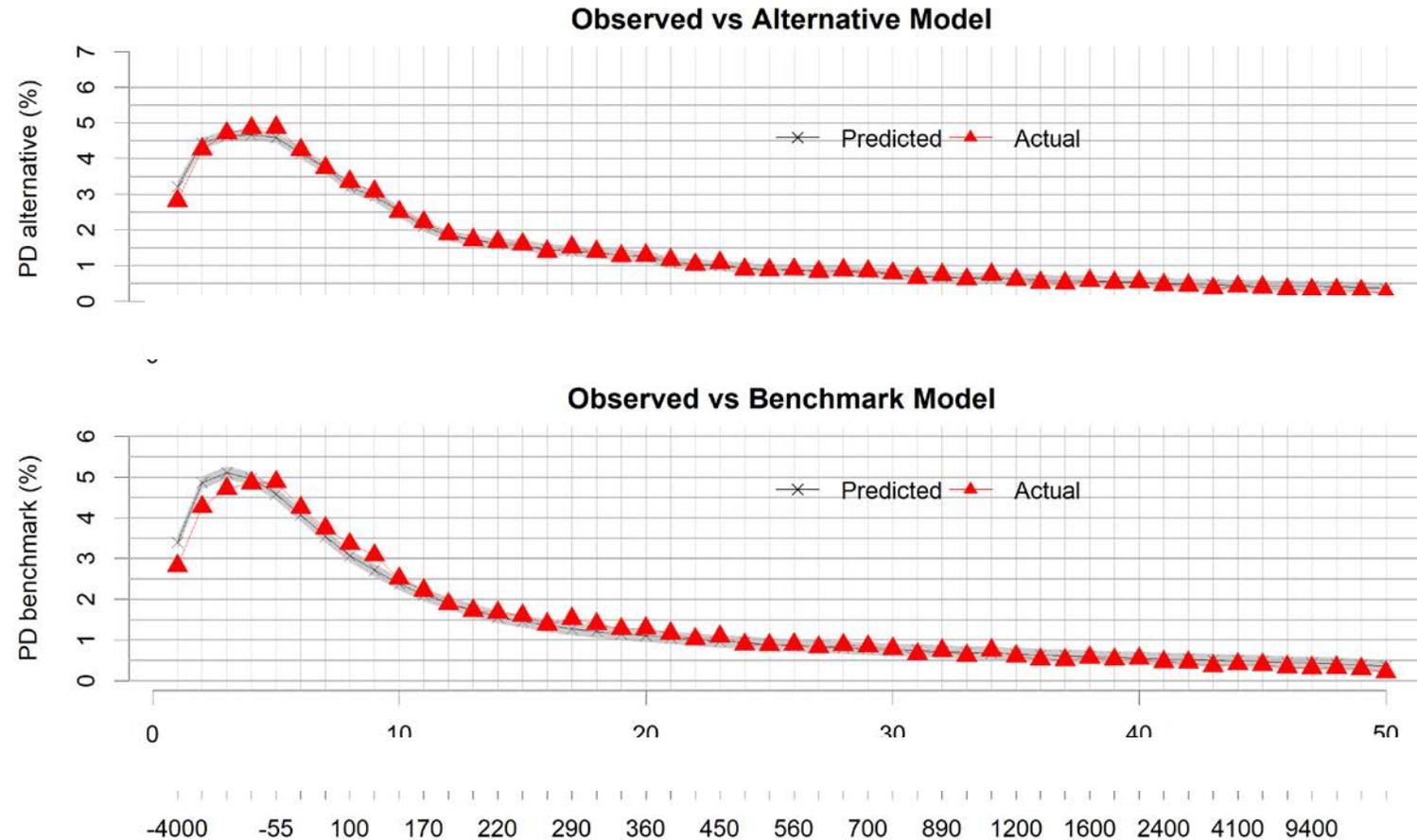
Data bucketing number above and corresponding variable value below

2.9 7.3 10 13 16 19 23 28 38 89

Cur Liab to Sales

New approach fits nonlinear relationship between EBITDA to interest expense and default better

SUMMIT
2018



5

Look at Outliers

Inspect cases where PDs are very different

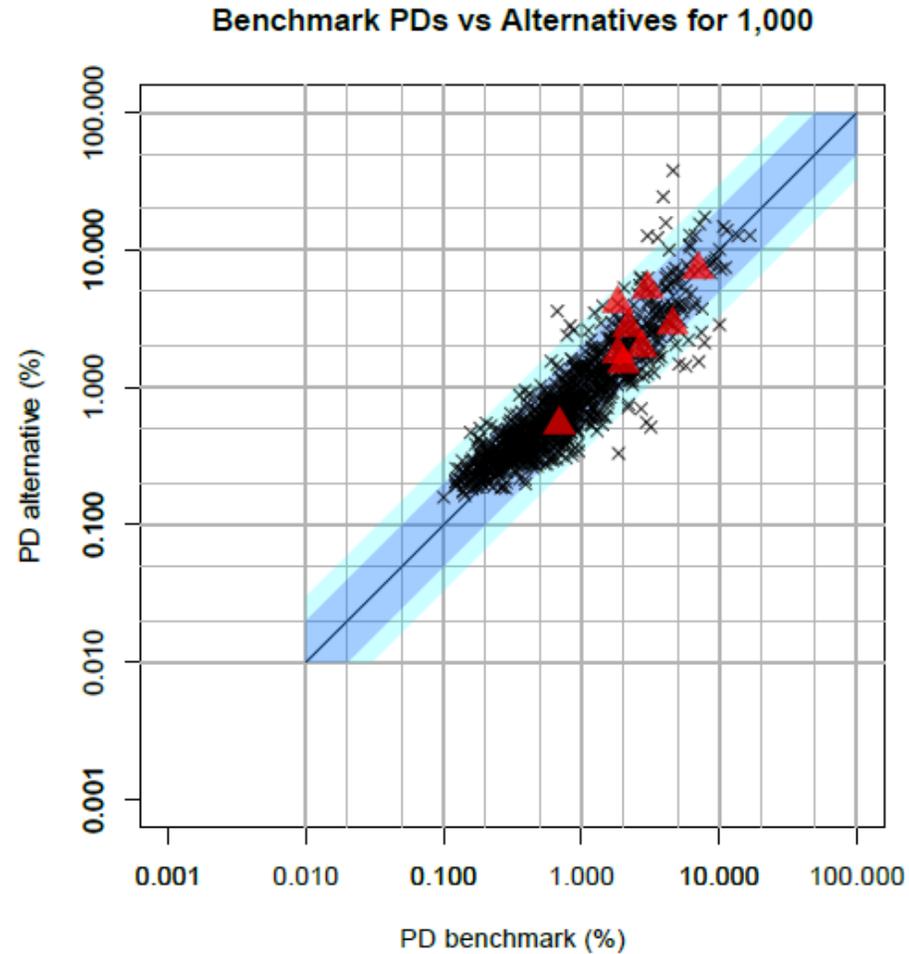


Figure 19: Alternative vs Benchmark

For example...



- » Black box nature of the models – lack of interpretability
- » Hard to anticipate model behavior outside of the data range

Case 1: A non-defaulted company in the Trade industry

EBITDA to Interest Expense: 4X

Return on Assets: -17%

Cash to Assets: 1%

Debt to (Debt plus Equity): 77%

Retained Earnings to Current Liability: -6X

Total Assets: \$500,000

Boosting PD = 0.2% (A3)

RiskCalc PD = 8.9% (Caa/C)

Case 2: A non-defaulted company in the Business Services industry

EBITDA to Interest Expense: 40X

Return on Assets: 212%

Cash to Assets: 10.5%

Debt to Debt plus Equity: 89%

Retained Earnings to Current Liability: 357X

Total Assets: \$5.8MM

Boosting PD = 13.7% (Caa/C)

RiskCalc PD = 0.54% (Baa3)

6

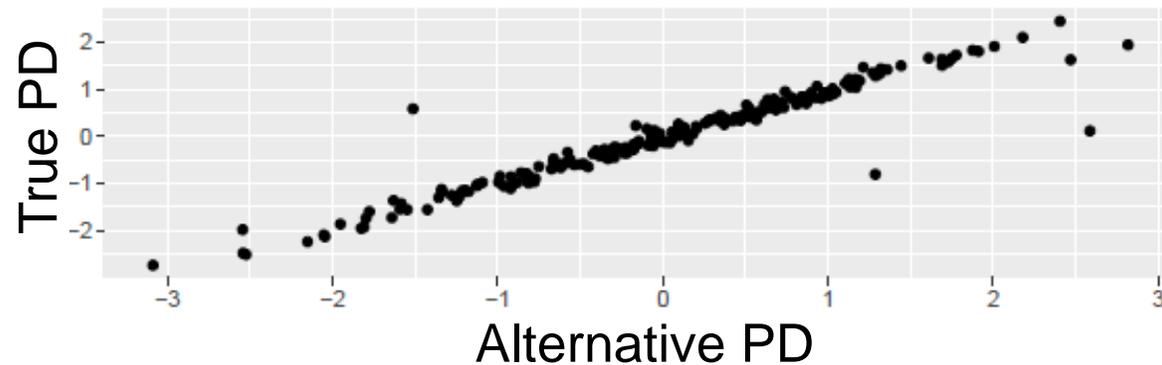
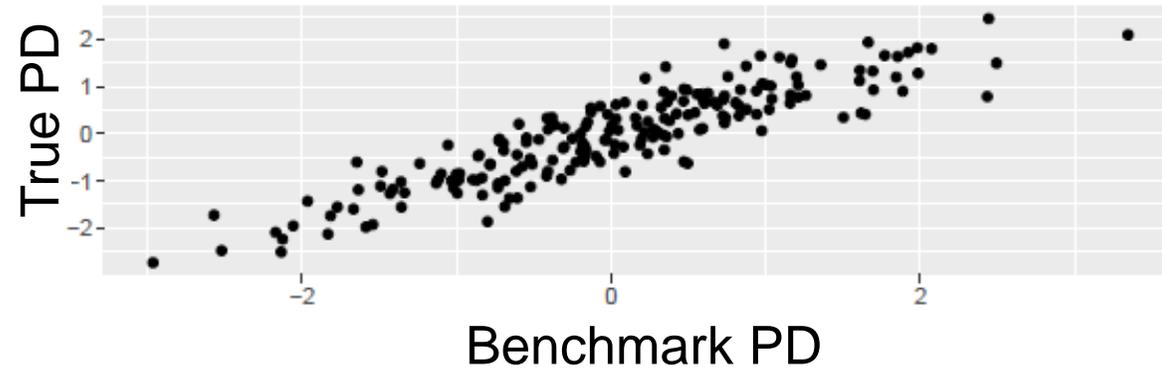
Combining the Approaches

How to use a really good signal, except when it is bad

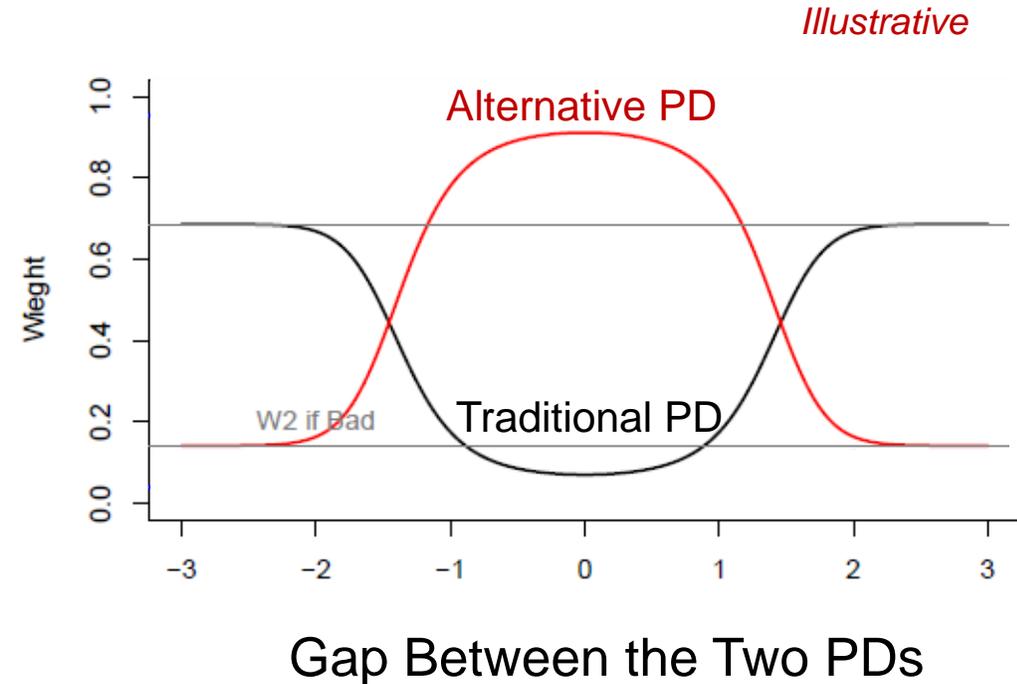
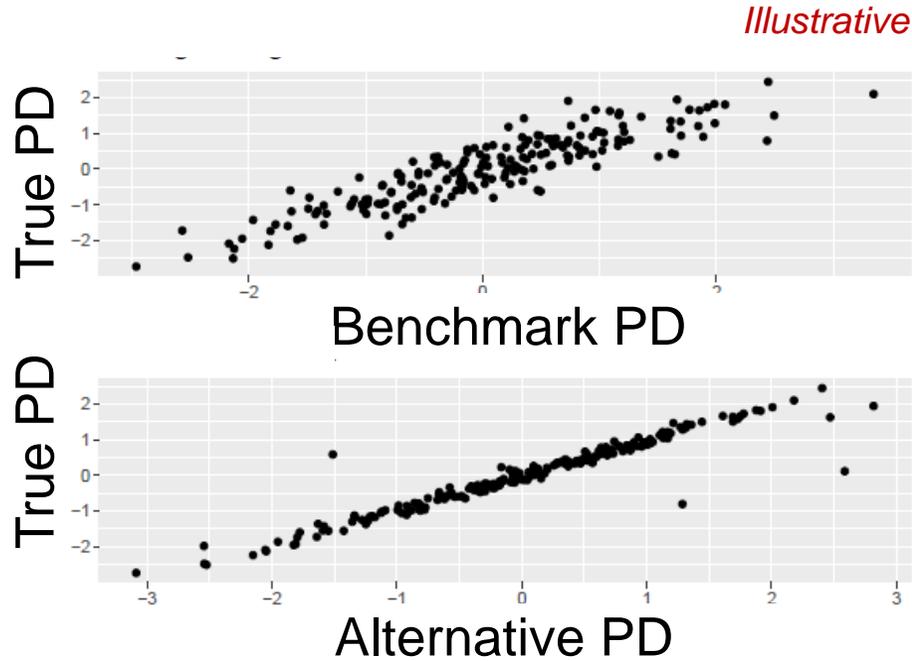
Suppose we have two measures of the same signal – e.g. the PD.

One signal is known to be much better most of the time, but it is sometimes faulty.

Illustrative

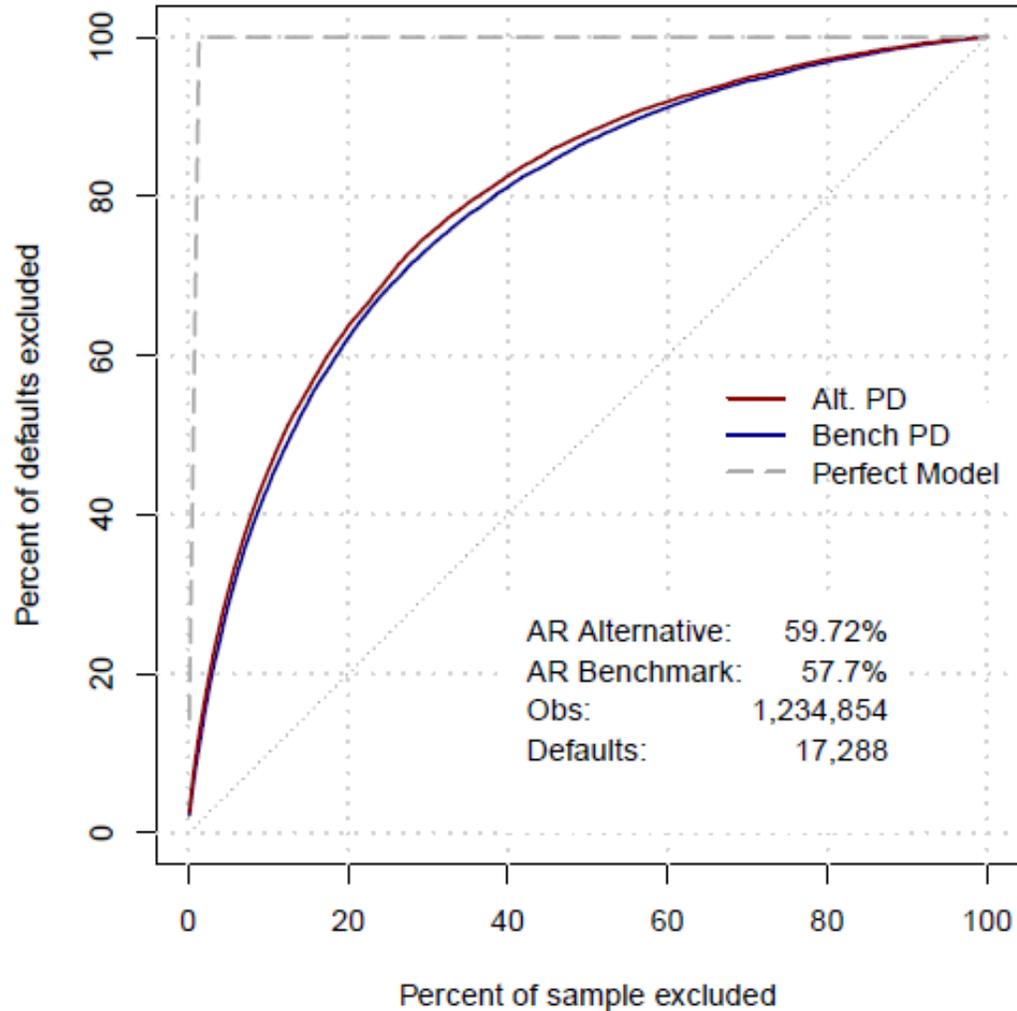


Bayesian approach lowers the weight on the second signal, as the gap between the two increases

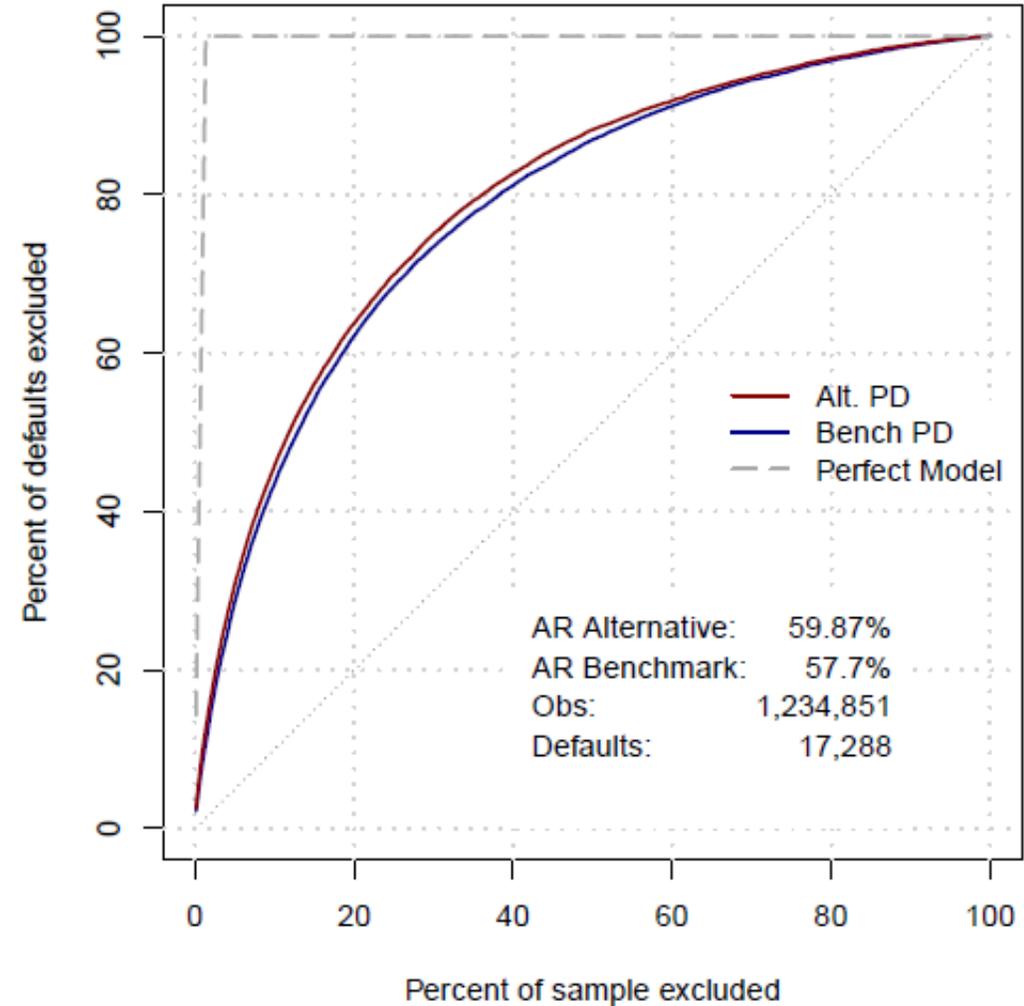


Combination improves power a bit

Highly Nonlinear Model vs. Traditional



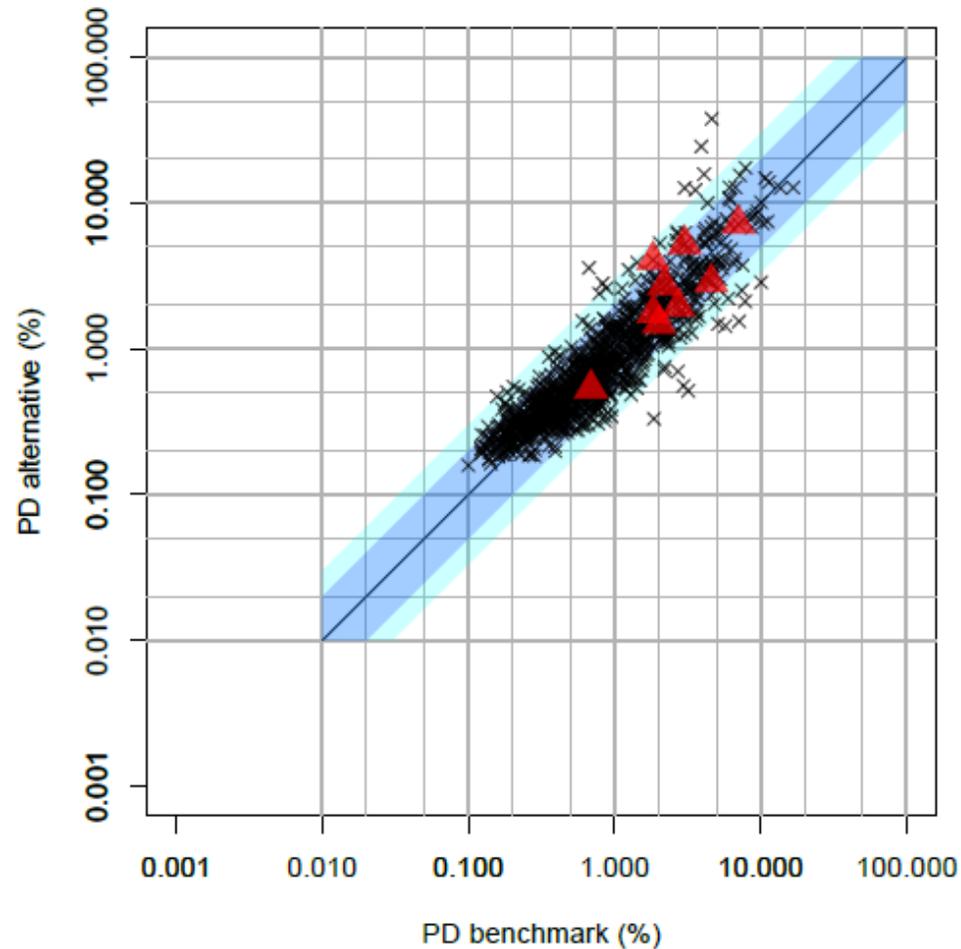
Combination vs. Traditional



Combination tightens the differences between the two

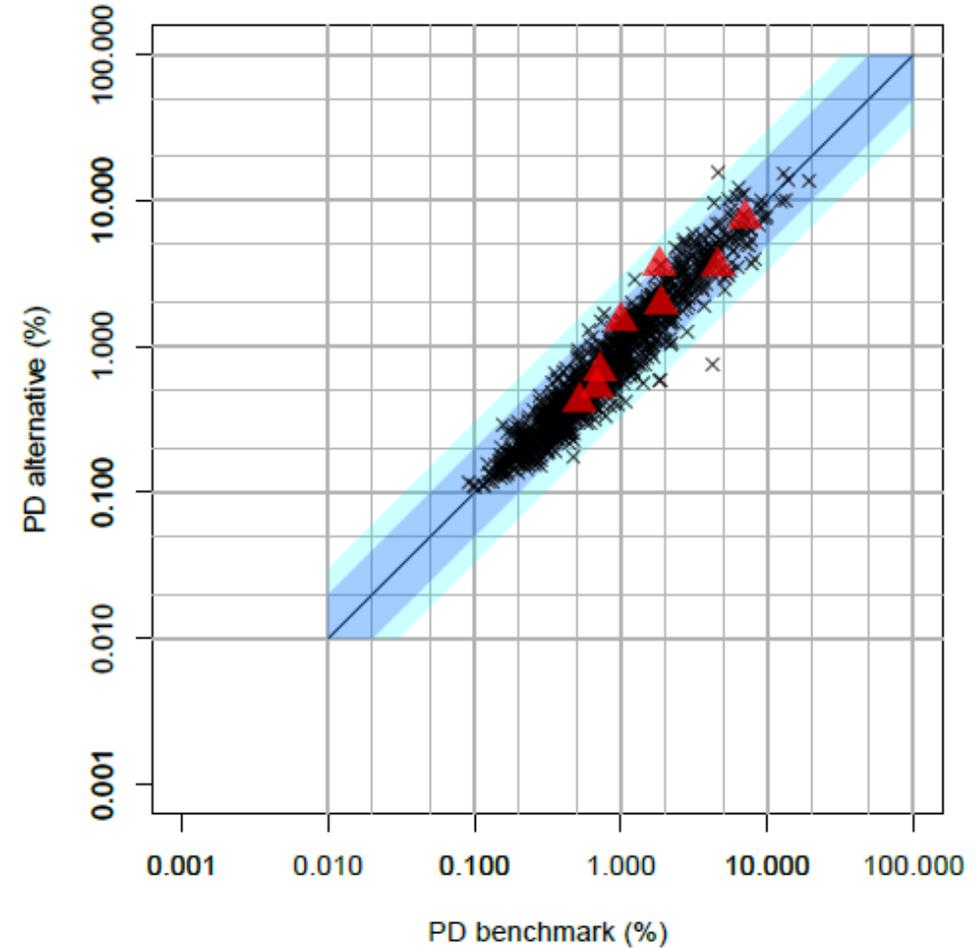
Highly Nonlinear Model vs. Traditional

Benchmark PDs vs Alternatives for 1,000



Combination vs. Traditional

Benchmark PDs vs Alternatives for 1,000



7

Million Dollar Difference

Model difference is worth a million dollars



Assumptions

\$10 billion portfolio

Loosening Credit Standards Causes

- » More loans to good borrowers (PPNR* Increases)
- » More loans to bad borrowers (Provisions Increases)

Net Income (NI) is the PPNR less Provisions

Central Default Tendency (CDT) of population is 2%

A bank that lends to everyone has no income:

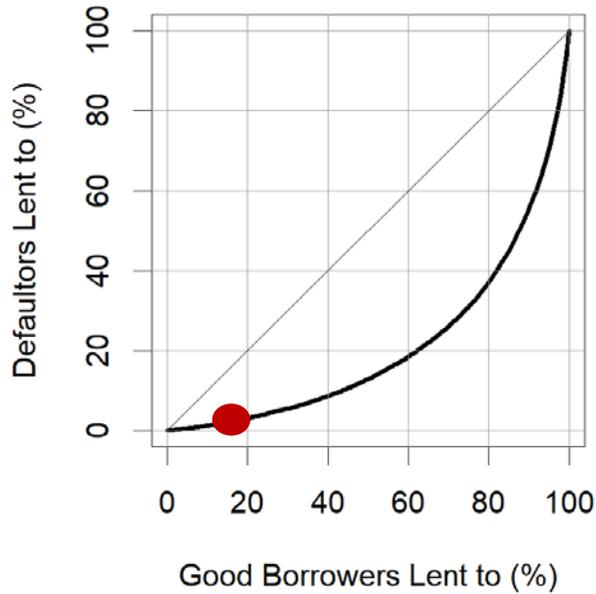
- » $Spread = \text{Central Default Tendency} * LGD / (1 - \text{Central Default Tendency})$

*PPNR is Pre Provisions Net Revenue

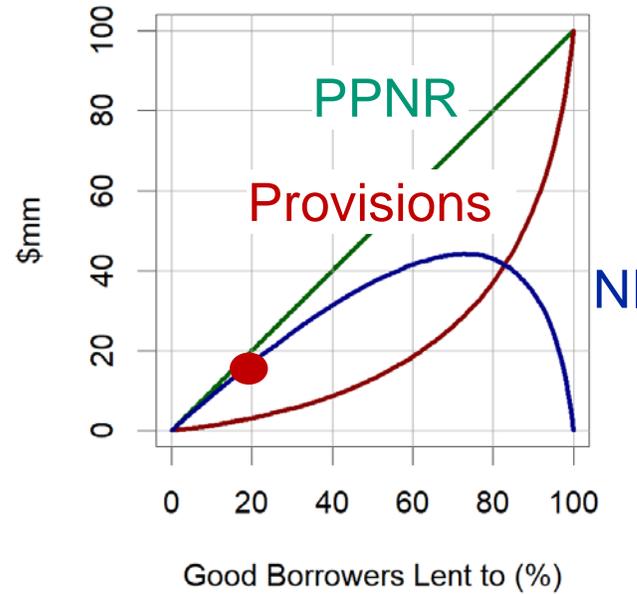
Tighter lending standards result in low provisions, but low PPNR



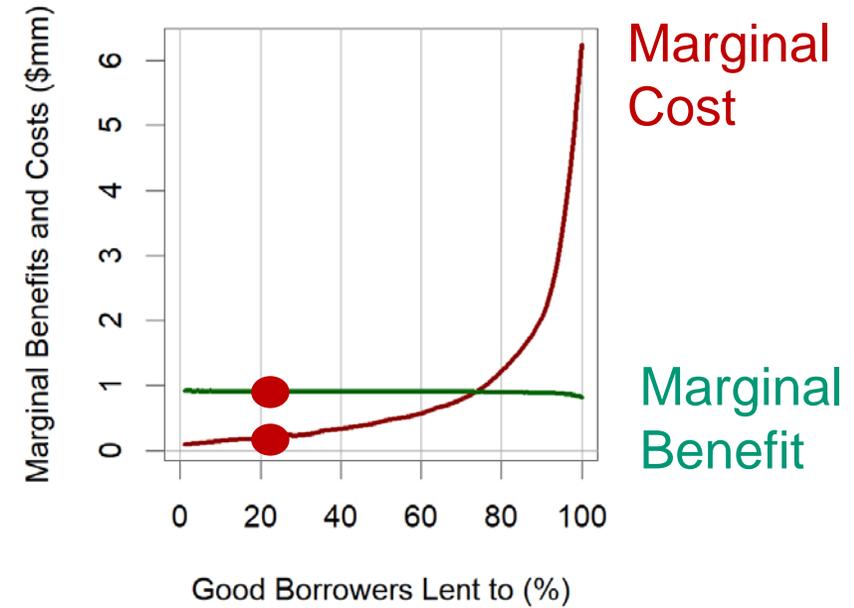
Impact of Lending Standards



Impact on Revenue



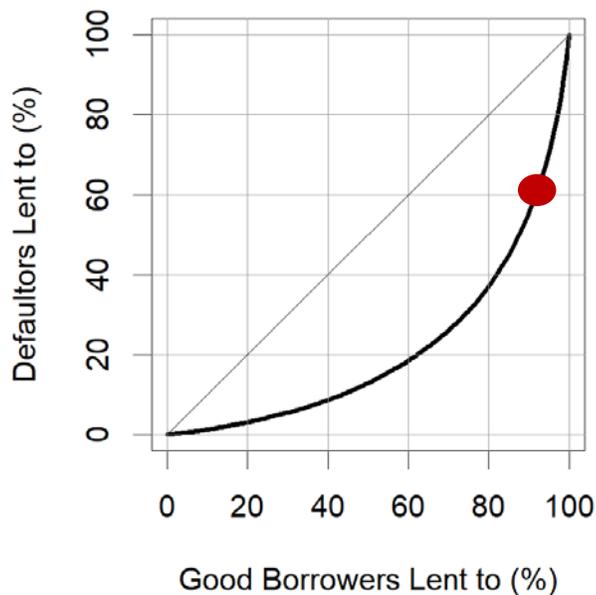
Marginal Cost and Benefit



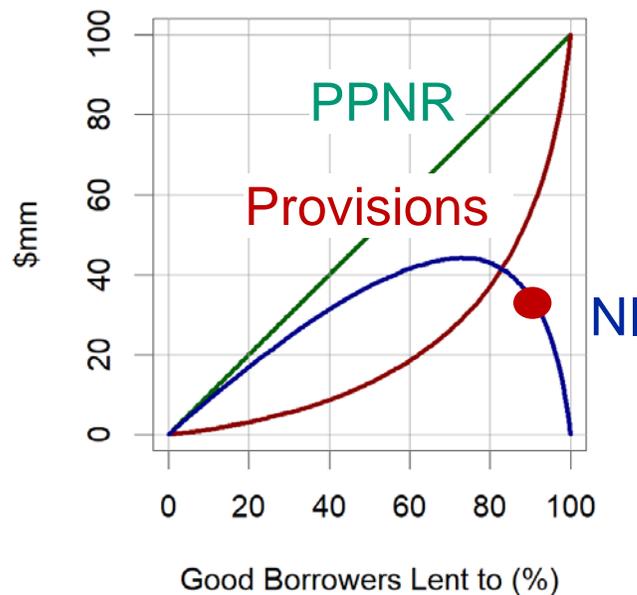
Loose lending standards result in large PPNR, but large provisions as well



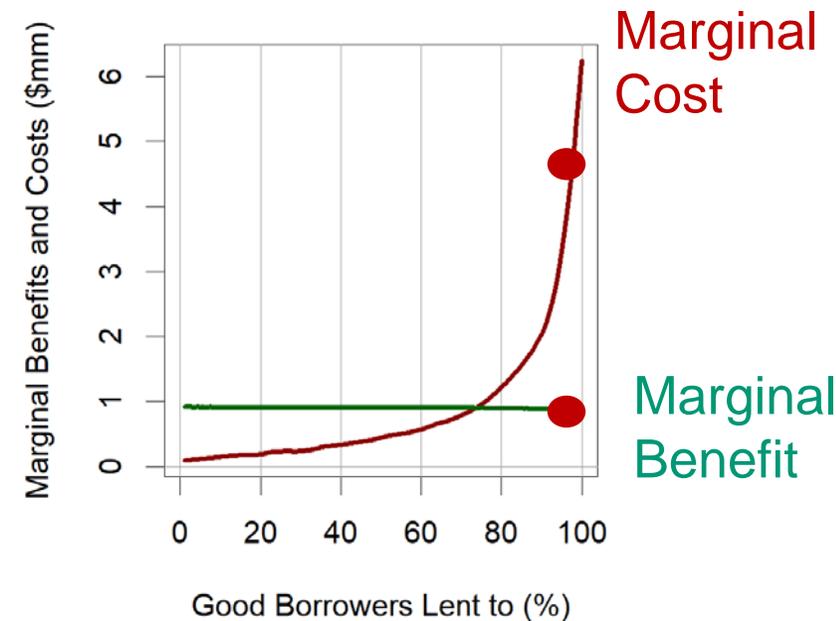
Impact of Lending Standards



Impact on Revenue



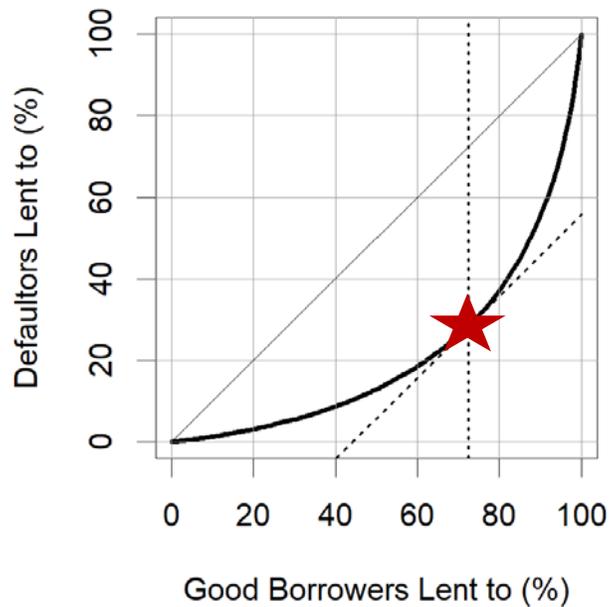
Marginal Cost and Benefit



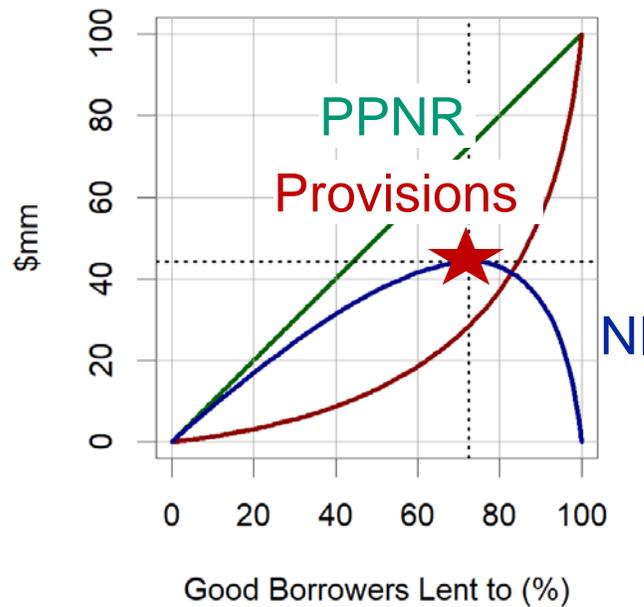
Setting marginal cost to marginal benefit optimizes net income



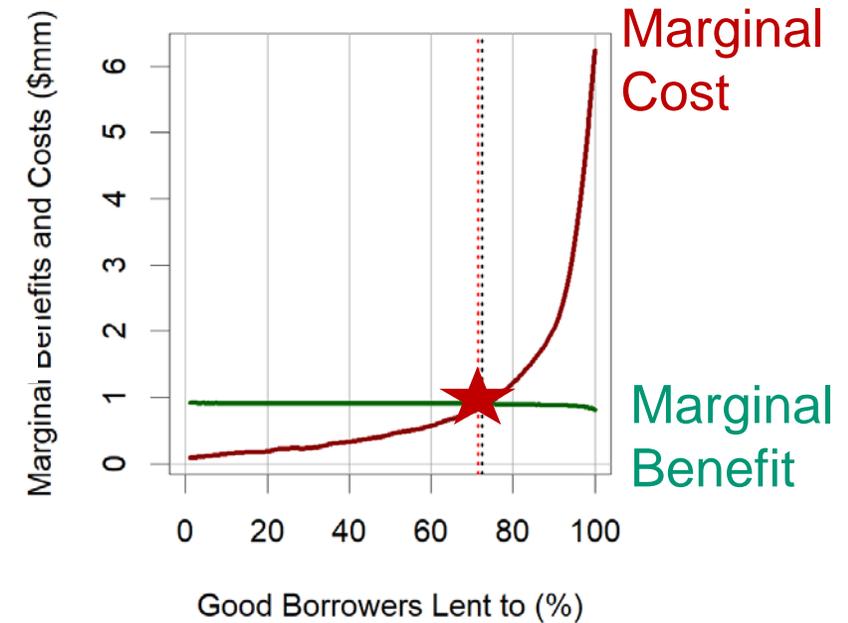
Impact of Lending Standards



Impact on Revenue



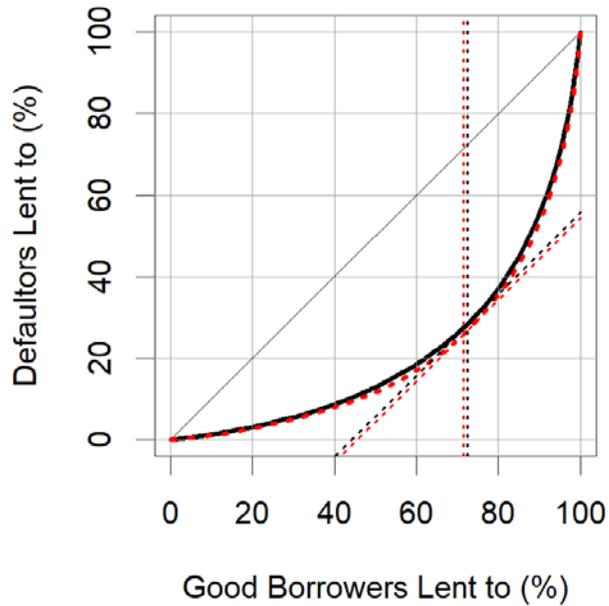
Marginal Cost and Benefit



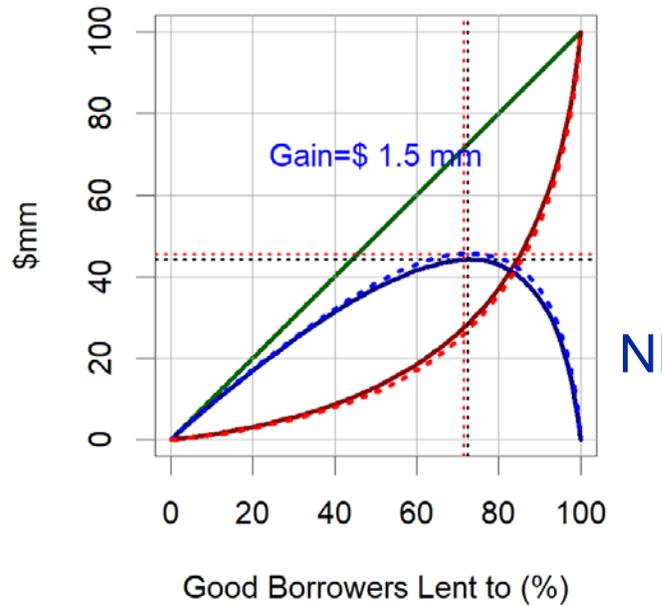
New model yields better cost curves worth \$1.5mm



Impact of Lending Standards

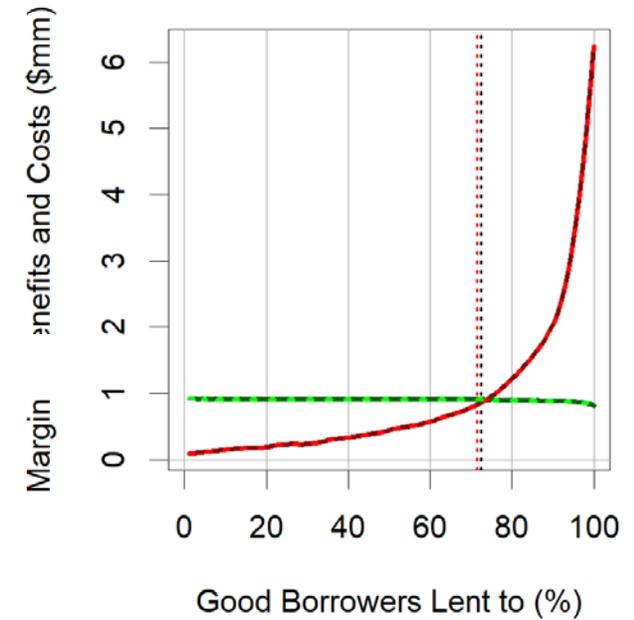


Impact on Revenue



NI

Marginal Cost and Benefit



More accurate new model produces \$1.454mm by turning away 2.8% more of the bad borrowers and only 1.4% more of the good borrowers.

New model yields better cost curves worth \$1mm

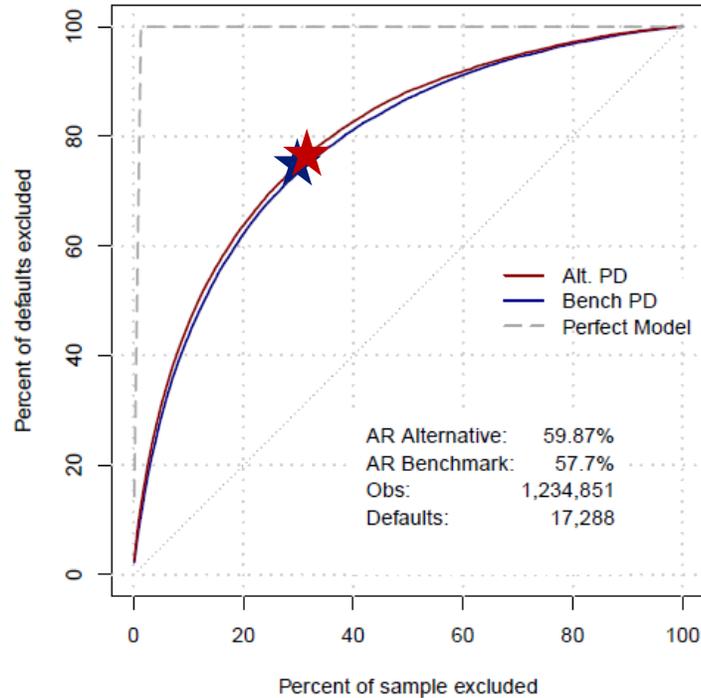


Figure 2: Cap Plot

Assumptions						
Average Default Rate			2%			
Loss Given Default			50%			
Benefit of a Good			1.02%			
Size of Portfolio			\$ 10,000,000,000			
Bad Borrowers Turned Away	Good Borrowers Turned Away	Bads Turned Away in Excess of Goods	Losses Avoided	Lost Income	Benefit of Model	
Traditional Model	71.7%	27.5%	44.2%	\$ 71,650,856	\$ 27,492,458.30	\$ 44,158,397.79
New Model	74.5%	28.9%	45.6%	\$ 74,531,467	\$ 28,918,421.47	\$ 45,613,045.44
Difference Model						\$ 1,454,647.65

More accurate, new model produces \$1.454mm by turning away 2.8% more of the “bad” borrowers and only 1.4% more of “good” borrowers.

8

Conclusion

Conclusion



- » In validating a highly nonlinear model, a *traditional nonlinear model* provides a useful reference.
- » Using known risk drivers to predict default helps achieve a transparent model.
- » Can use a weighted average of the two models to achieve even better results.
- » Care must be taken to evaluate the performance across multiple dimensions.
- » Modern software and hardware makes the process easier.
- » Small differences in AR can be worth a lot of money.
- » Do not need to sacrifice transparency.

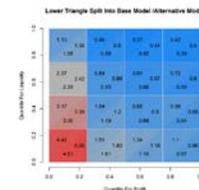
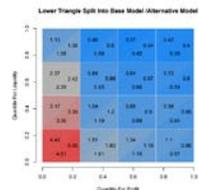
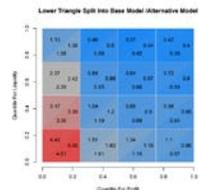
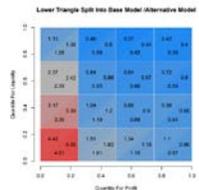
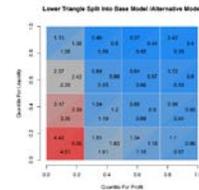
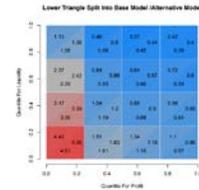
Extra Credit: interaction assessment for each pair of risk drivers

Risk Driver 1

Risk Driver 2

Risk Driver 3

Risk Driver 4



Risk Driver 1

Risk Driver 2

Risk Driver 3

Risk Driver 4

Appendix: What is PPNR?

The term is found in the CCAR methodology documentation.

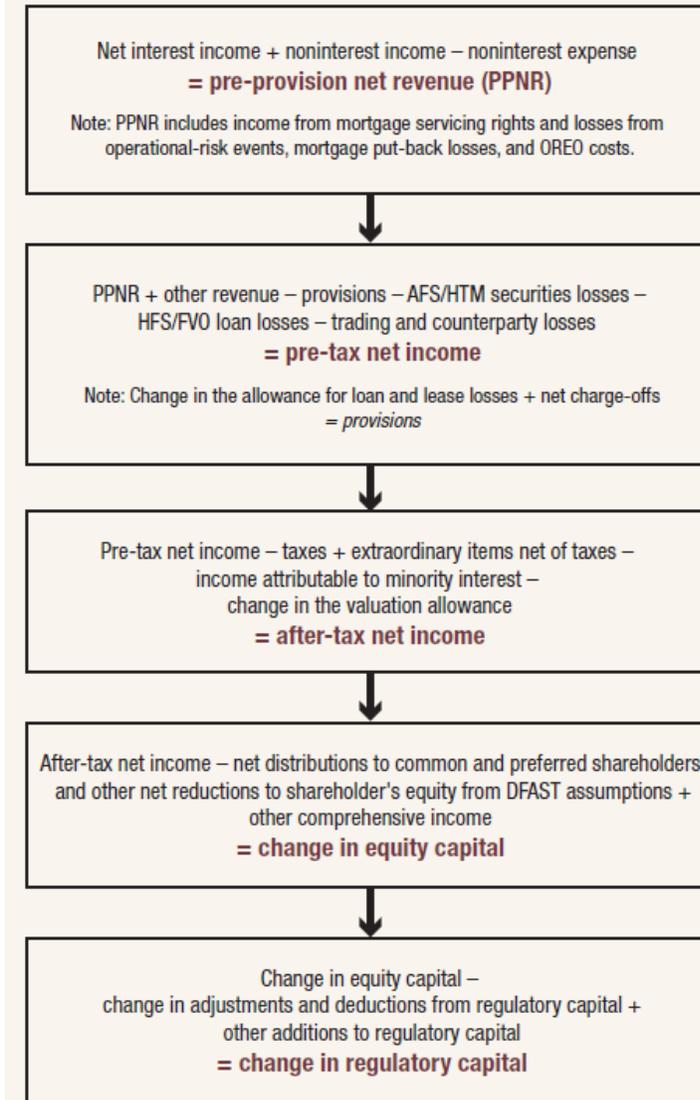
PPNR is net interest income plus noninterest income less noninterest expense.

and

Pretax Net Income is approximately PPNR less Provisions.

Source: *Dodd-Frank Act Stress Test 2016: Supervisory Stress Test Methodology and Results*

Figure 8. Projecting net income and regulatory capital



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