MOODY'S ANALYTICS

SUMMIT 2018

Validating and Understanding a Highly Nonlinear Machine Learning Model

Douglas W. Dwyer, Managing Director | Moody's Analytics

Agenda

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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	Deep Neural Networks	Option pricing theory
Natural Language Processing	Generalized Additive Models (Traditional Nonlinear Model)	Hierarchical Bayesian models
Kernel Methods	Support Vector Machines	Bias correction methods
	Nearest Neighbor	Structural Equation Modeling
	Random Forests	Structural Estimation
	Boosting (New Highly Nonlinear Model)	

Core validation principals

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

Recipe for validating a highly nonlinear PD model

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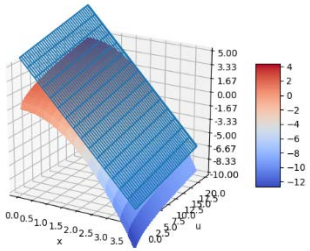
ML PD Model



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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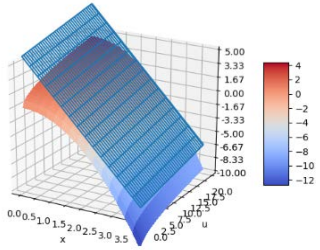
Ingredients

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



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To garnish

Labels and Formats

Method

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Recipe for validating a highly nonlinear PD model

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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.

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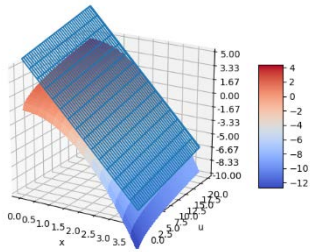
4) Look at “higher order effects” and validate “final model.”

ML PD model



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3

Why this Approach Works

Why this approach works

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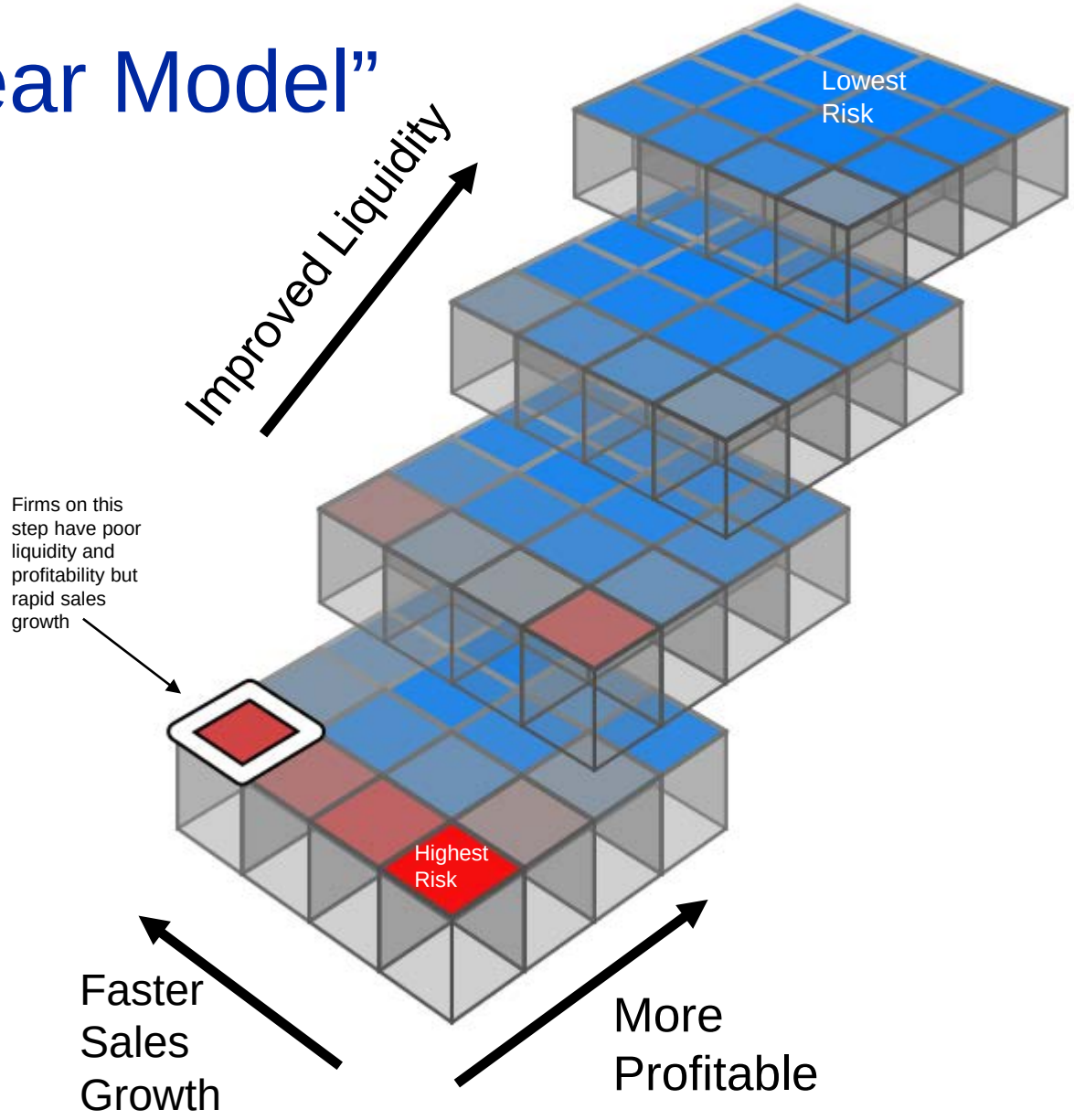
- We have an objective and concrete outcome variable -- Default
- Well-established set of risk drivers
- Large “panel” dataset
- “Credit Cycle” is treated separately

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.



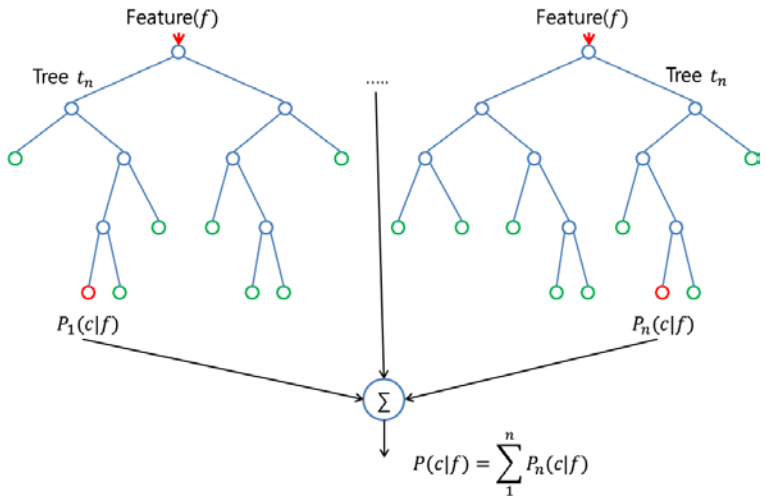
Highly nonlinear models: decision tree-based ensemble learners

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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Raw ratios + sector
Ratios imputed by median

- Boosting AR = 51%
- Probit AR = 38*%

Raw ratios + sector
Ratios imputed by median and windsorized (1% each)

- Boosting AR = 59.7%
- Probit AR = 48.9%

Percentiles of ratios + sector

- Boosting AR = 59.7%
- Probit AR = 53.5%

Full Transform

- Boosting AR = 59.7%
- GAM AR = 57.7%

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

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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
					100.00	438.00

Table 4: Statistics

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PD_bench					
T					
Number					
PD_alt					
PD_bench					
Defaults					
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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	

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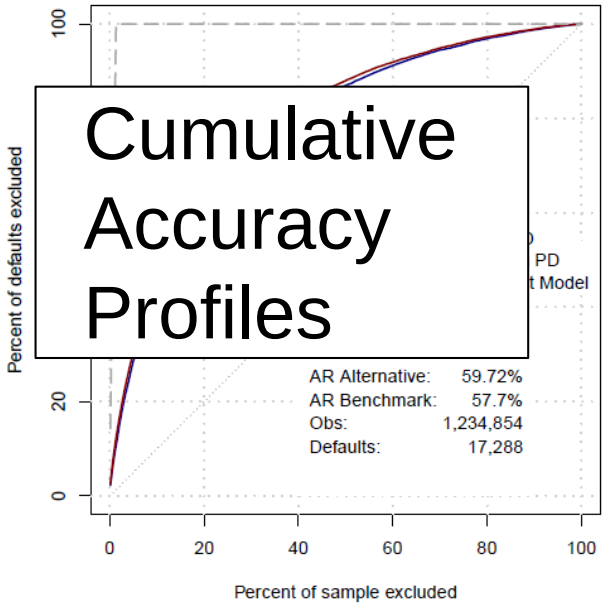

Cumulative Accuracy Profiles

Figure 2: Cap Plot

Provides back

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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

	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
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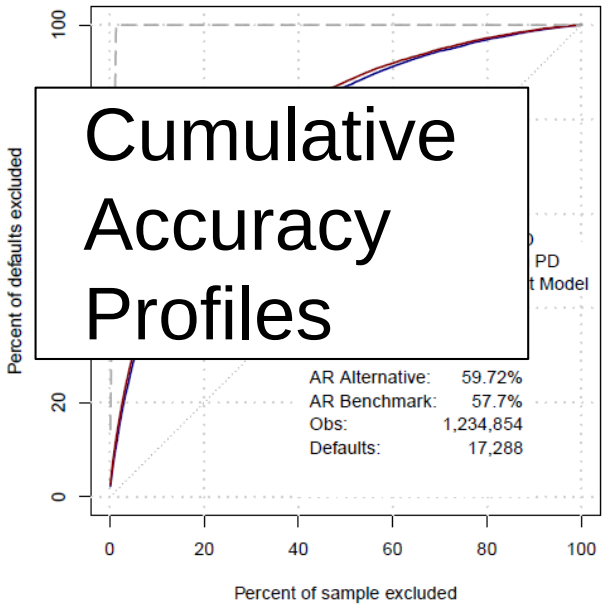
Trade	272,277				
Transportation	49,040	623	53.67	50.44	3.23
Unassigned	21,184	325	58.96	52.55	6.41
Utilities	14,359	70	63.93	54.98	8.95

Performance Stats “by Cut”



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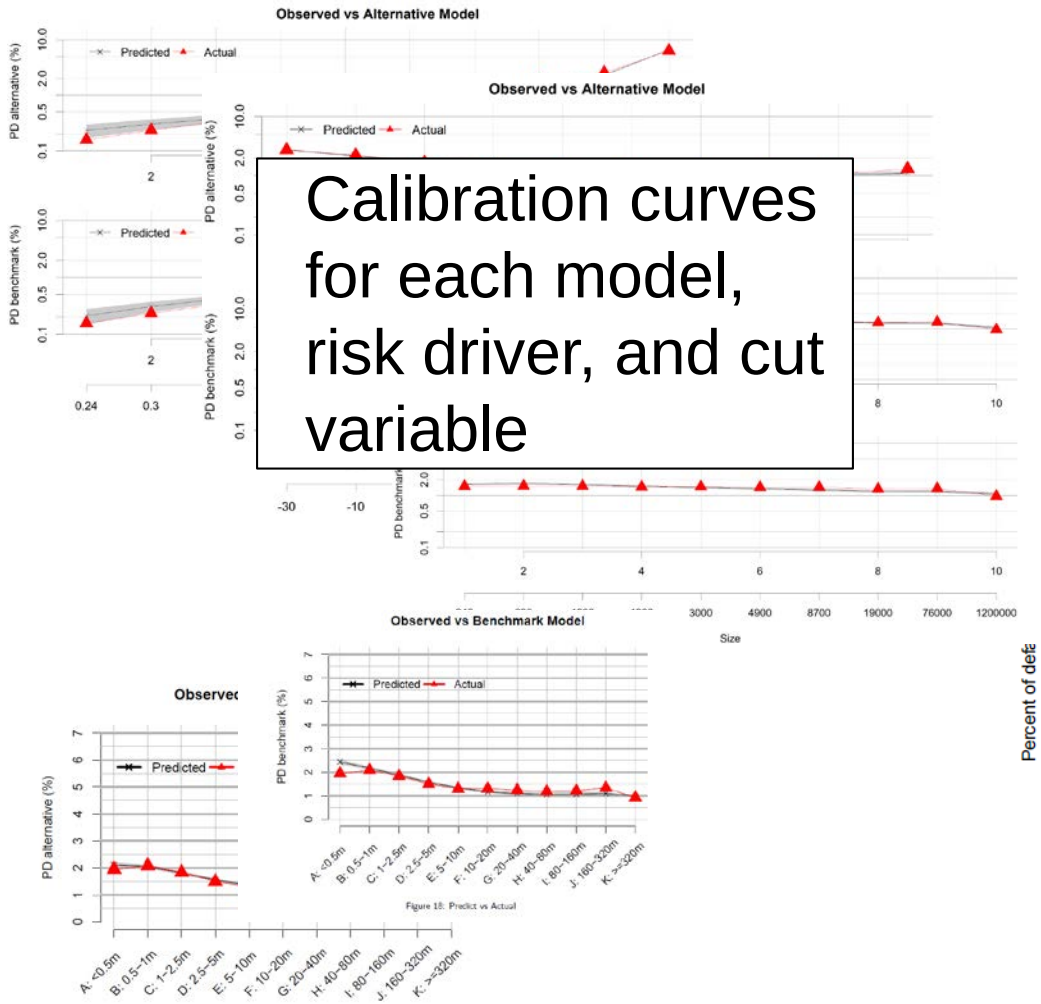

Calibration curves for each model, risk driver, and cut variable

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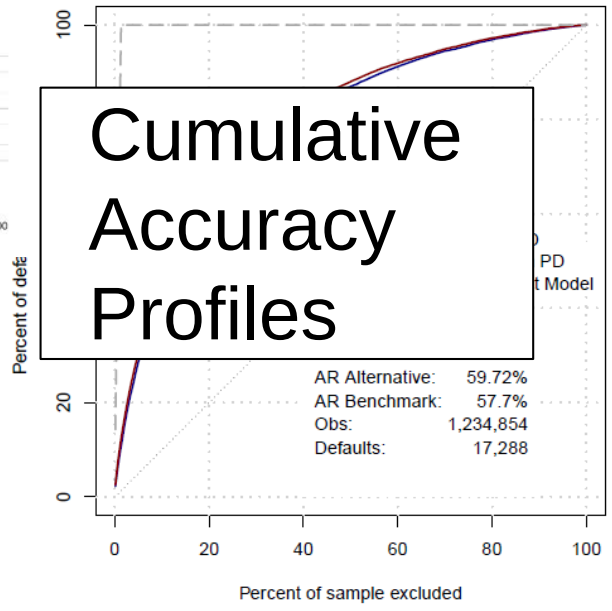

Cumulative Accuracy Profiles

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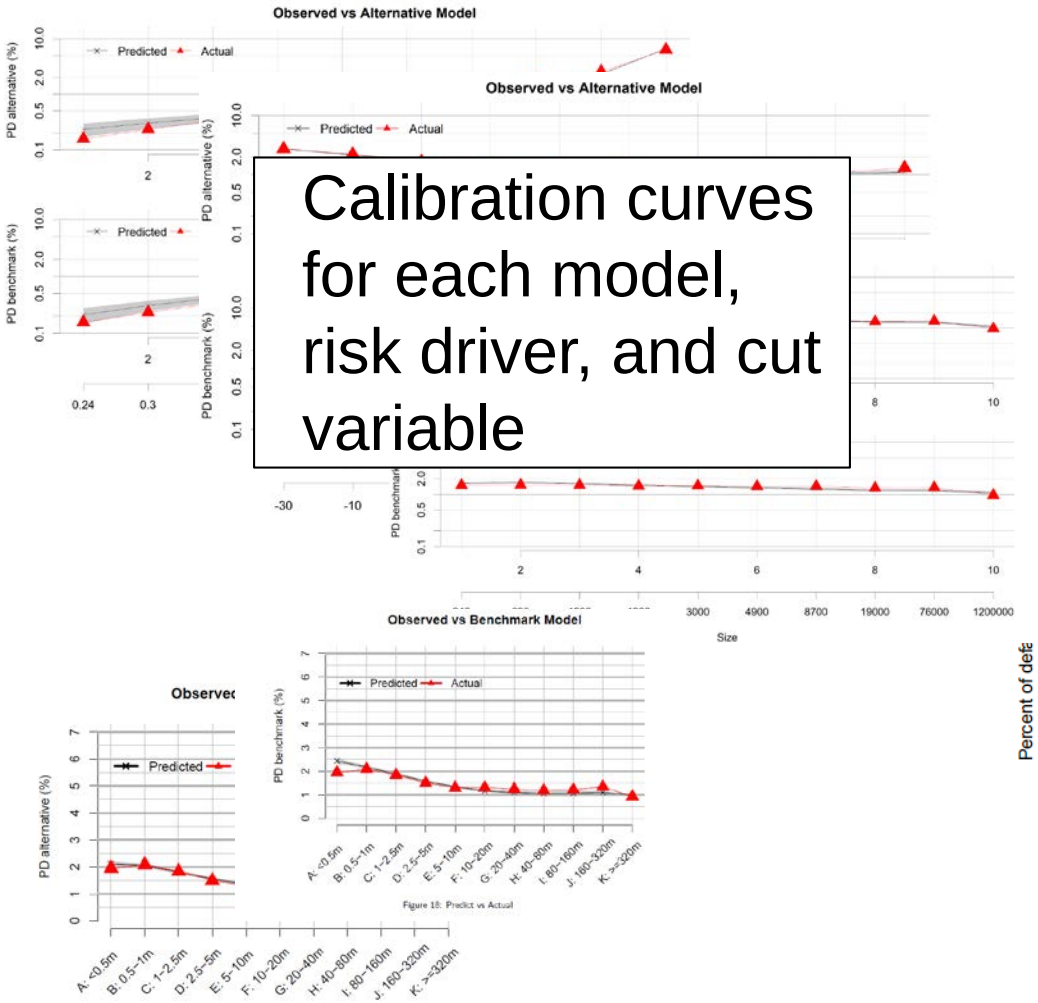

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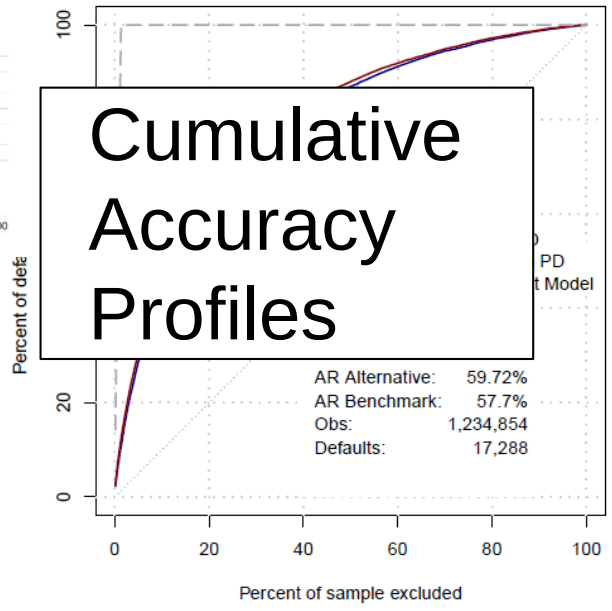

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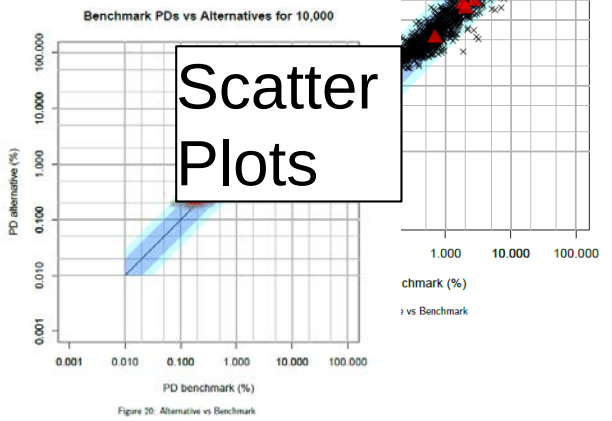

Scatter Plots

Findings

Boosting model delivers better CAP plot

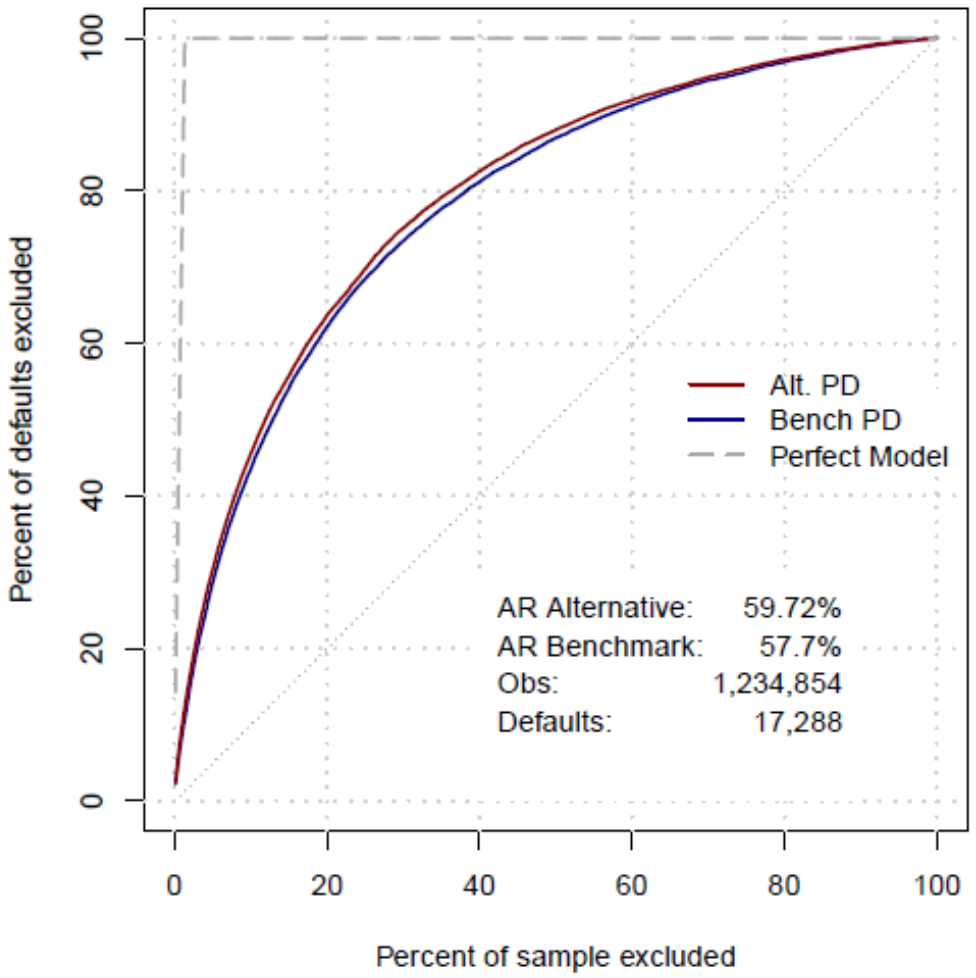

Figure 2: Cap Plot

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

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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

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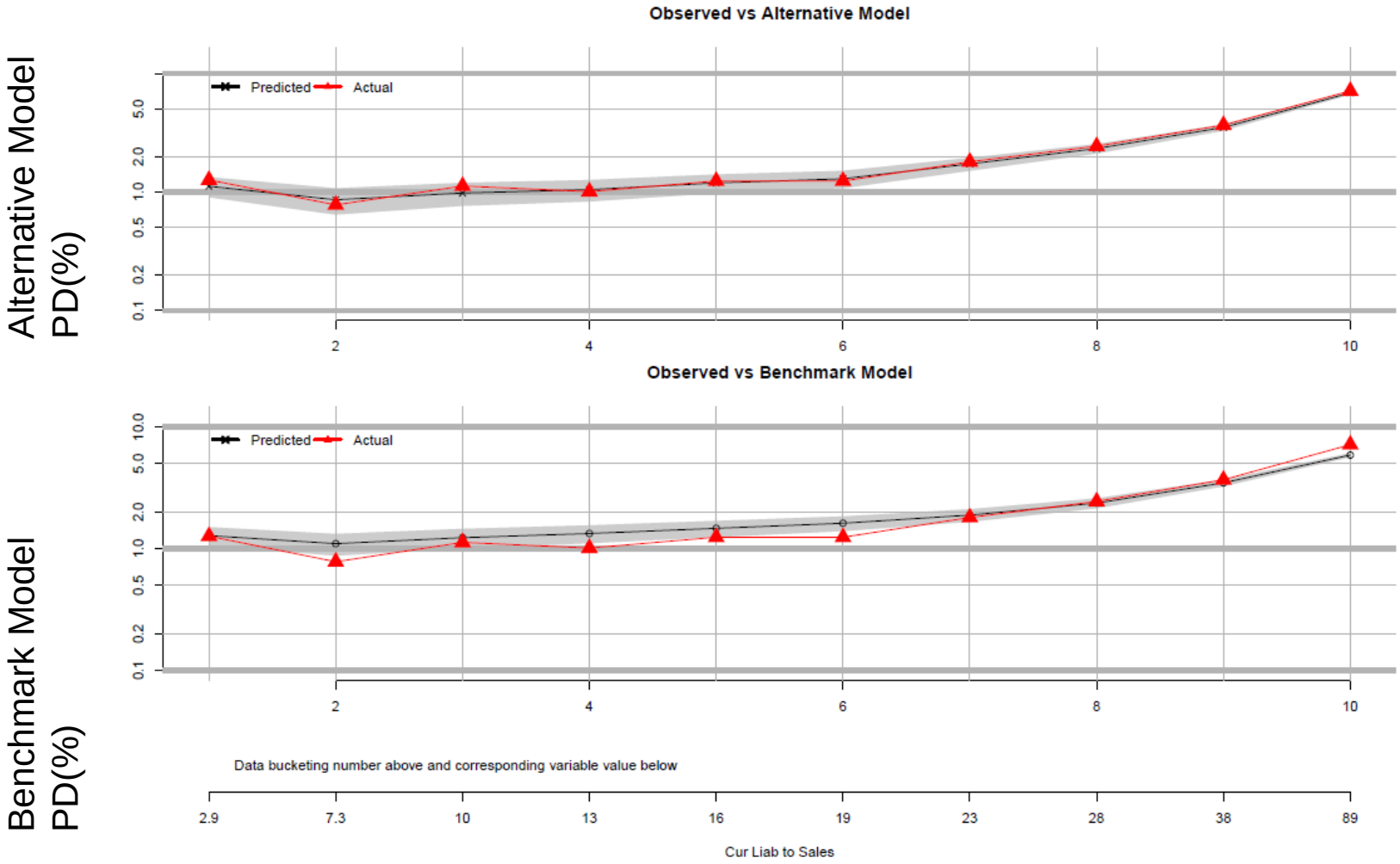
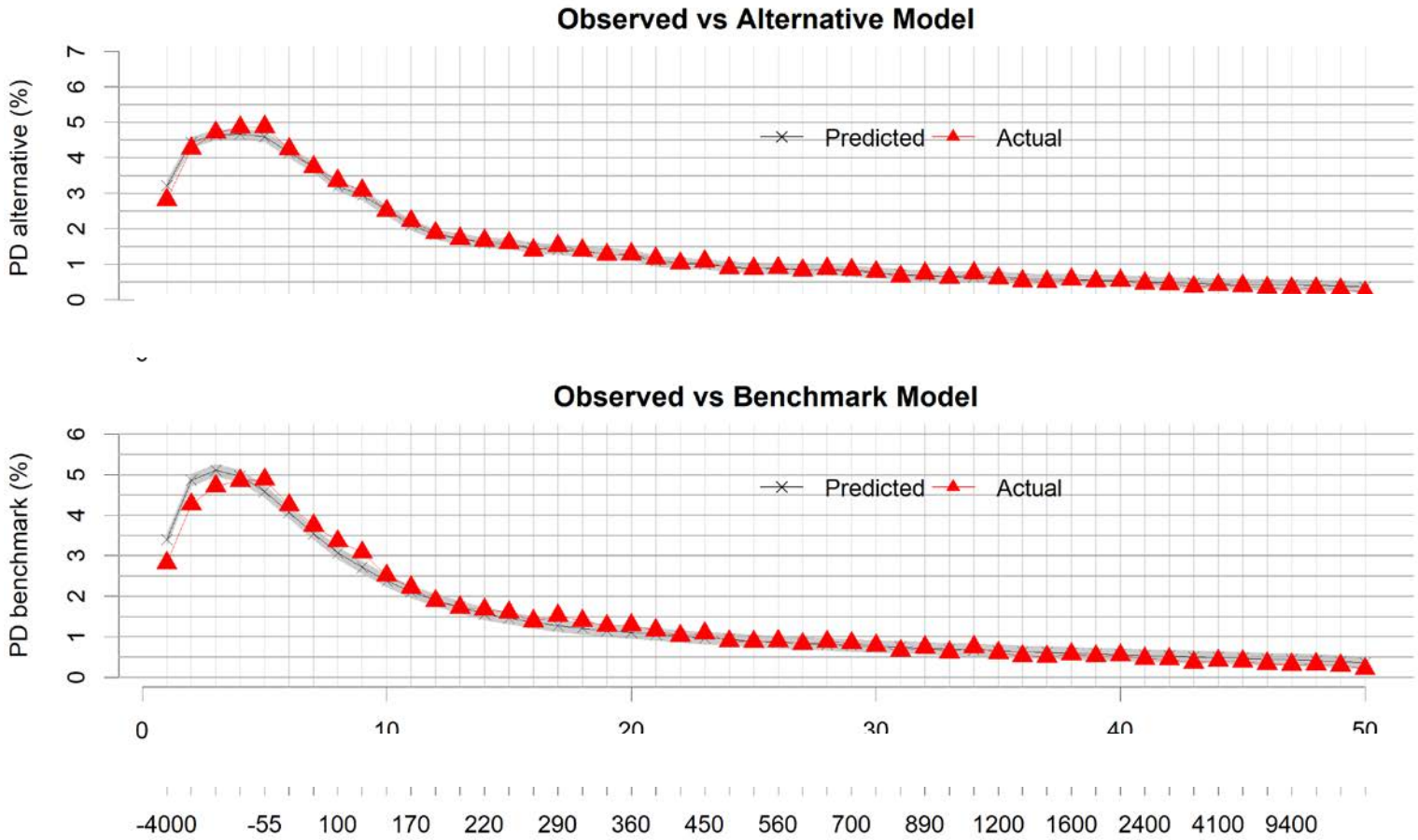
Traditional Nonlinear Model underweights Current Liabilities to Sales in Construction

Construction Only



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



5

Look at Outliers

Inspect cases where PDs are very different

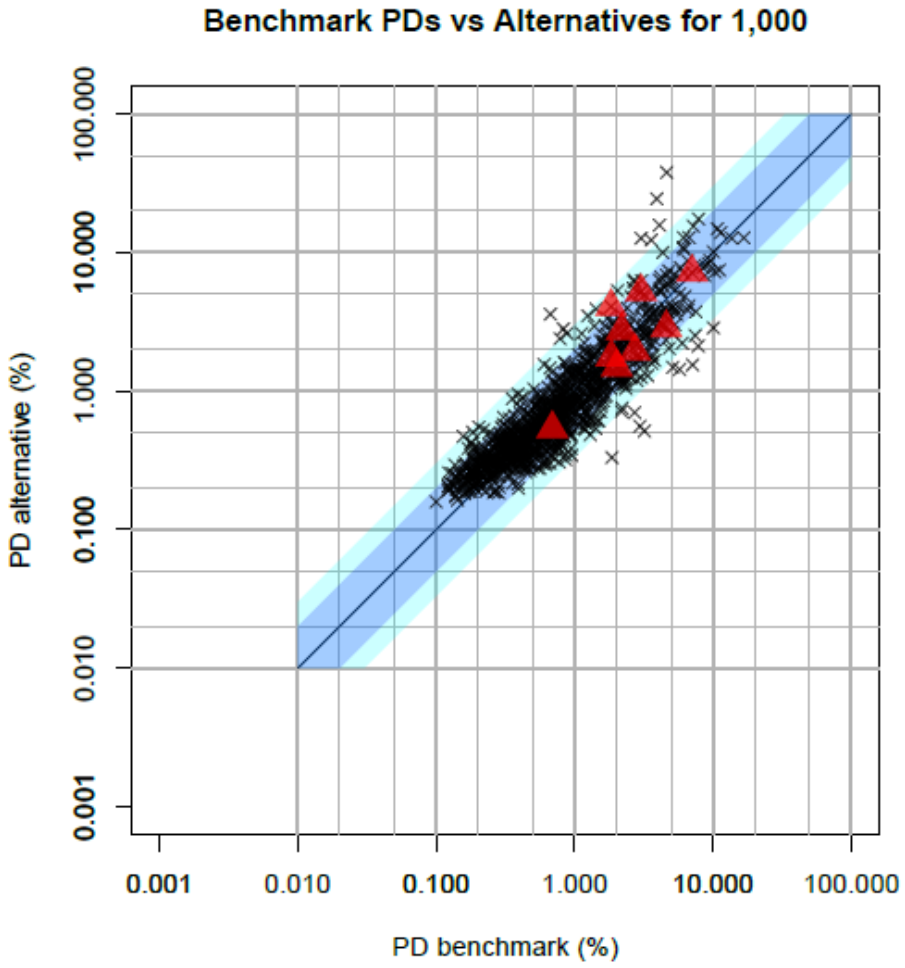


Figure 19: Alternative vs Benchmark

For example…

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- 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

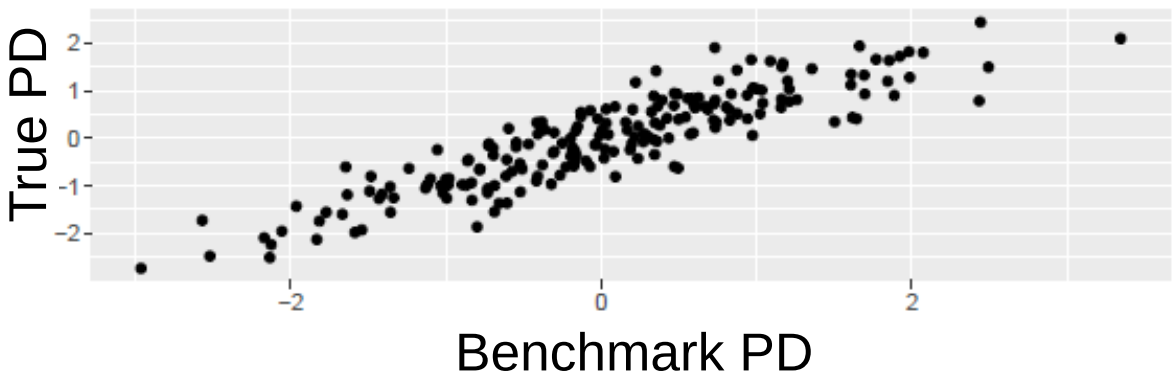
Combining the Approaches

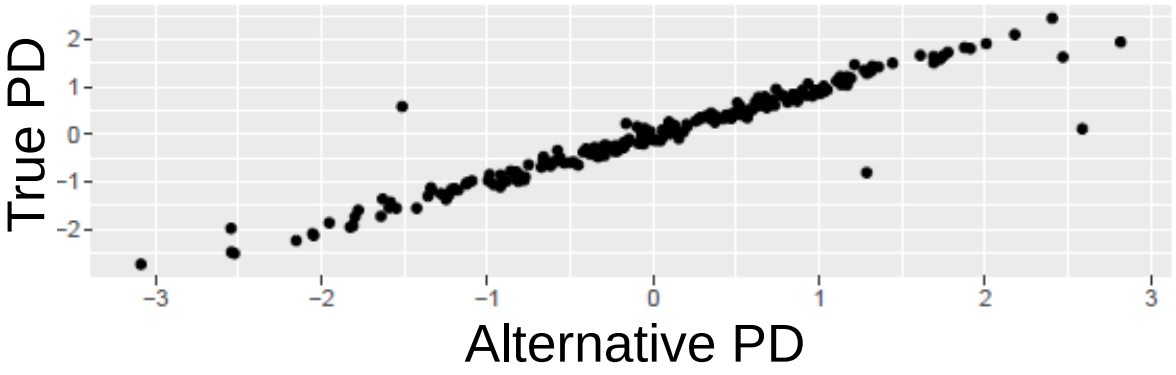
How to use a really good signal, except when it is bad

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

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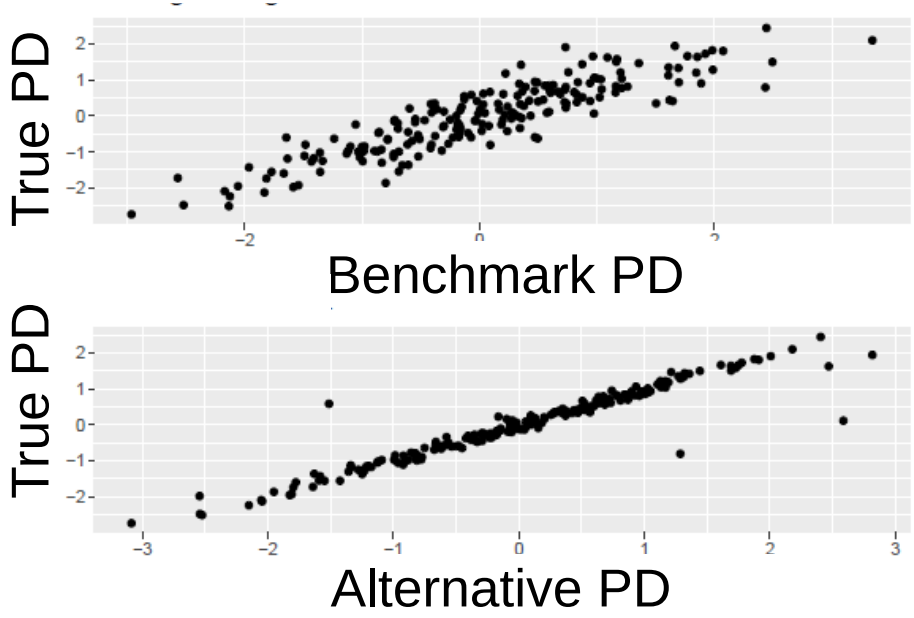
Illustrative



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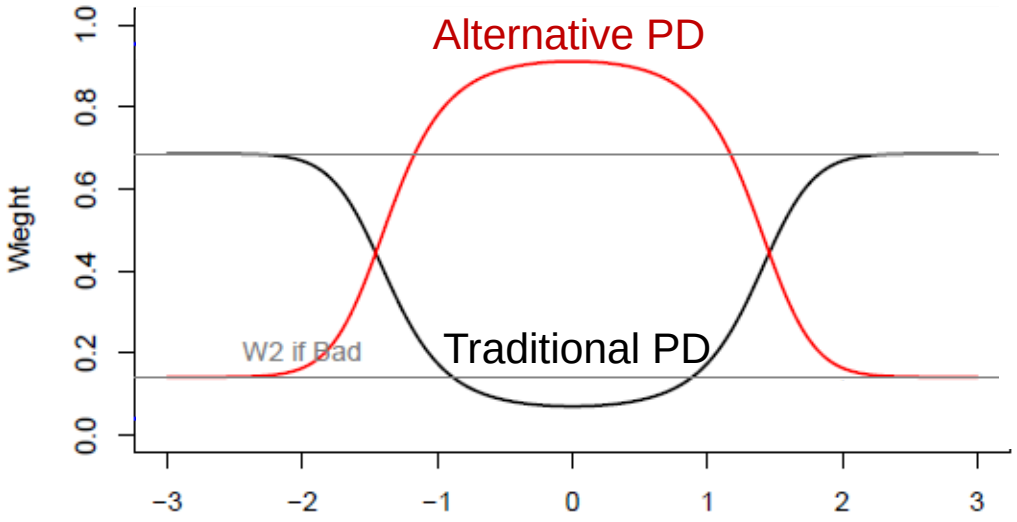

Gap Between the Two PDs

Combination improves power a bit

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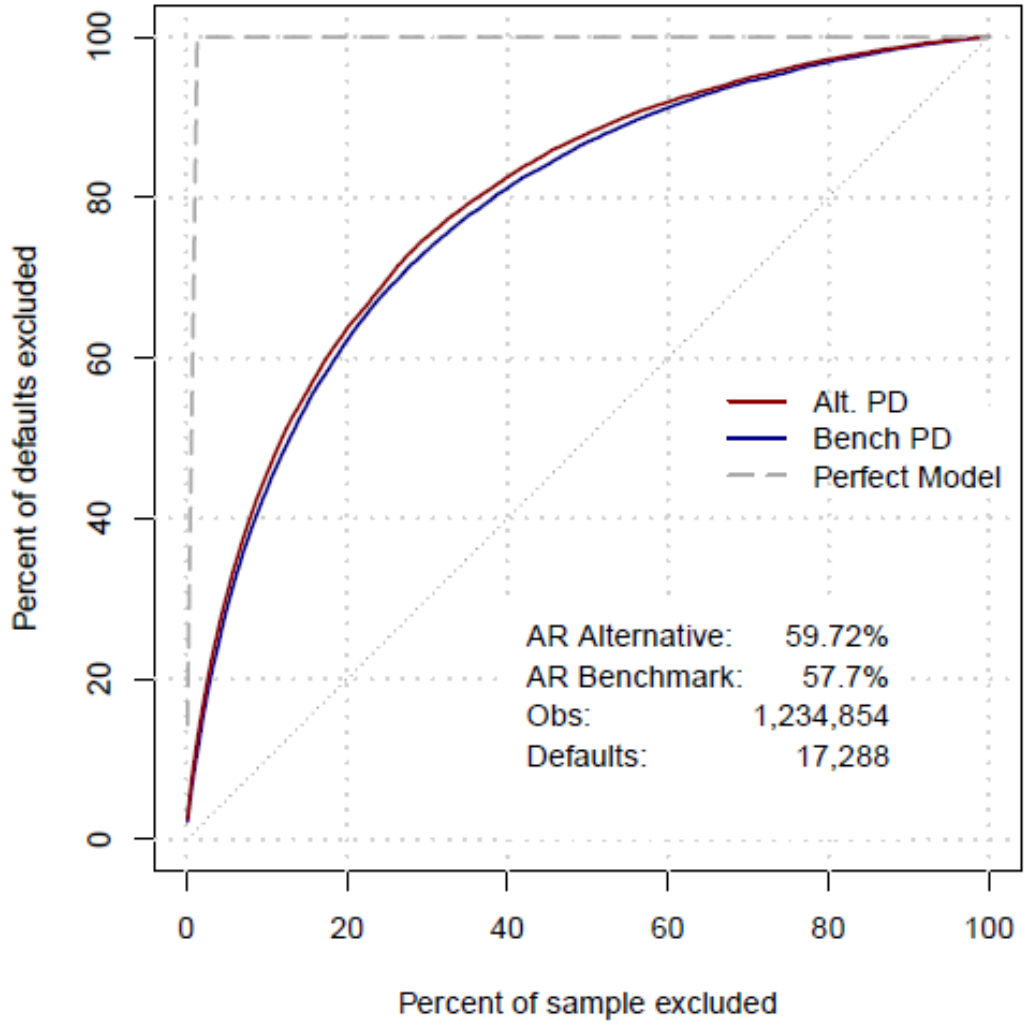
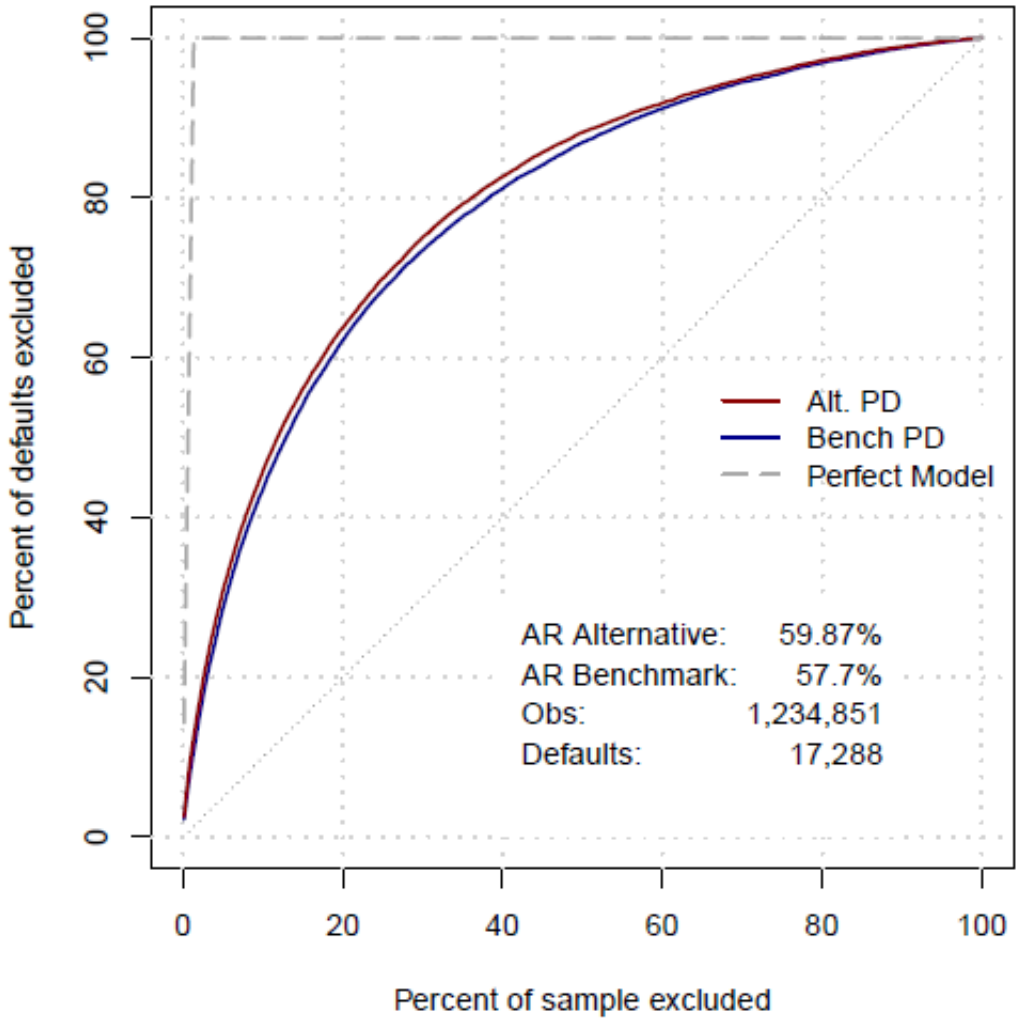
Highly Nonlinear Model vs. Traditional



Combination vs. Traditional



Combination tightens the differences between the two

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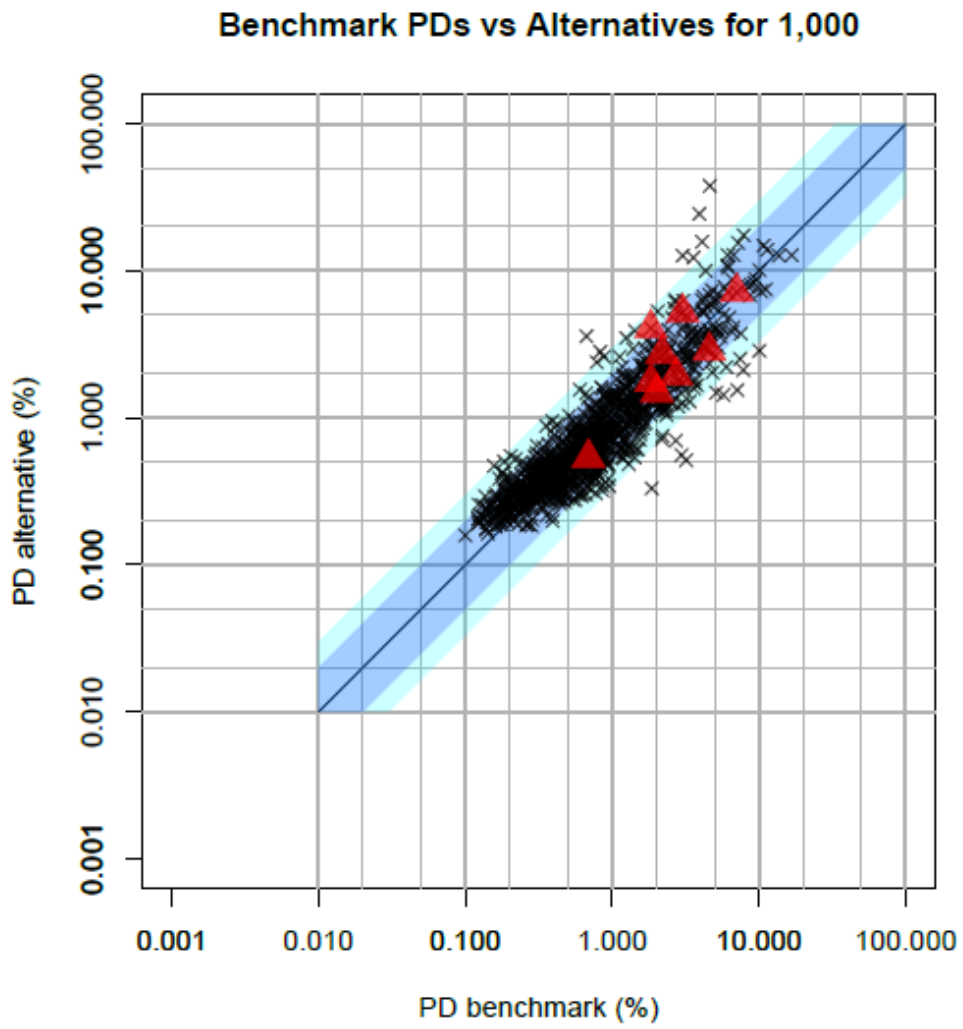
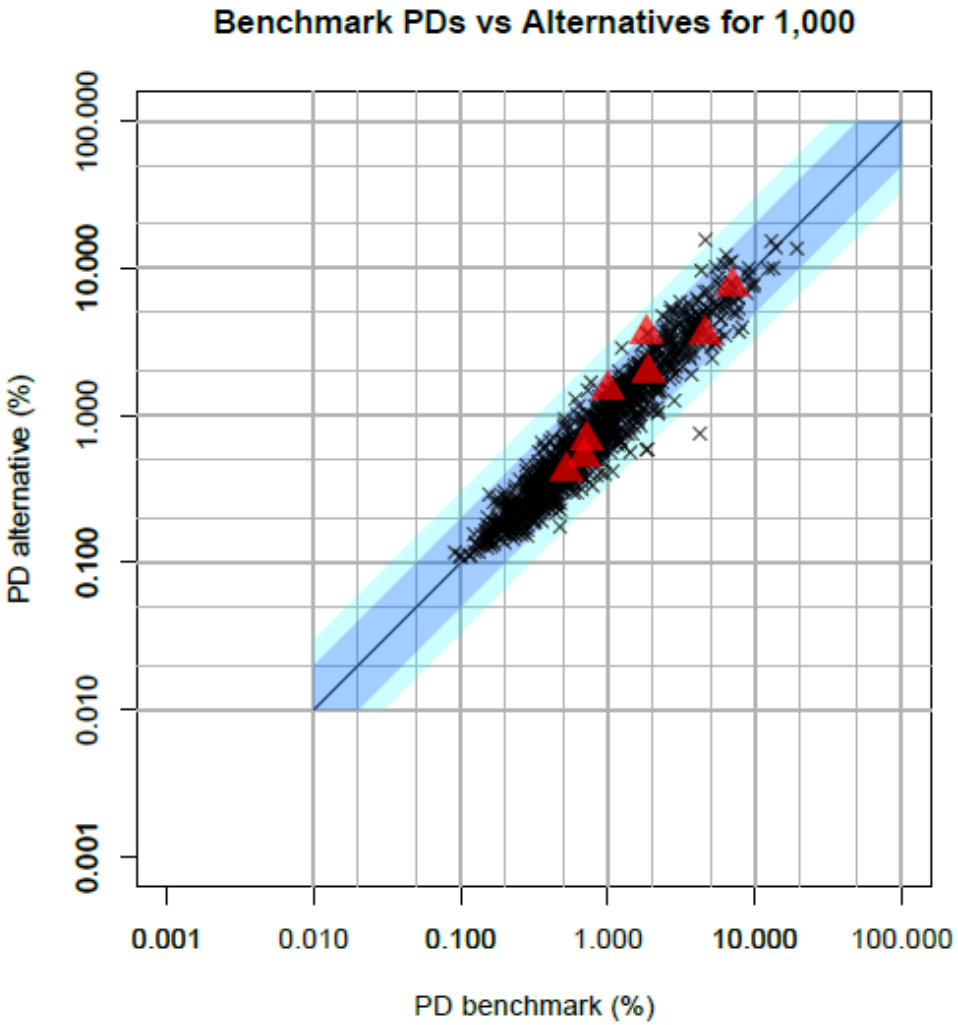
Highly Nonlinear Model vs. Traditional



Combination vs. Traditional



7

Million Dollar Difference

Model difference is worth a million dollars

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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

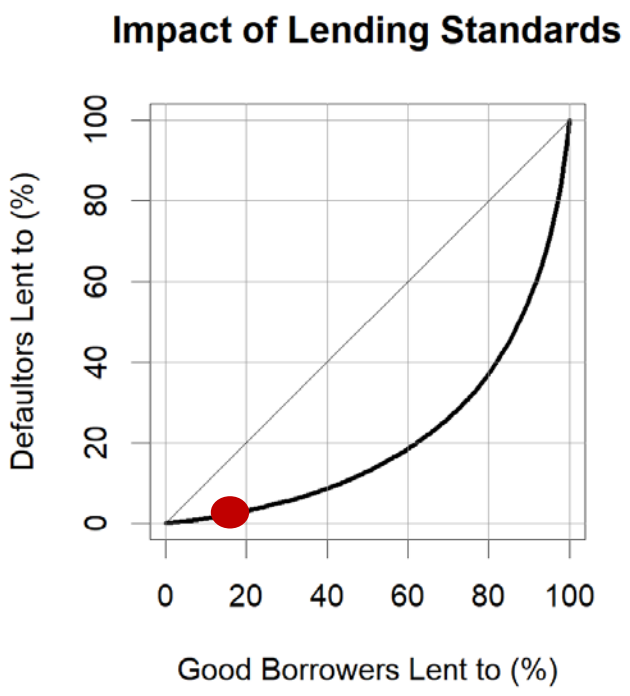
Central Default Tendency (CDT) of population is 2%

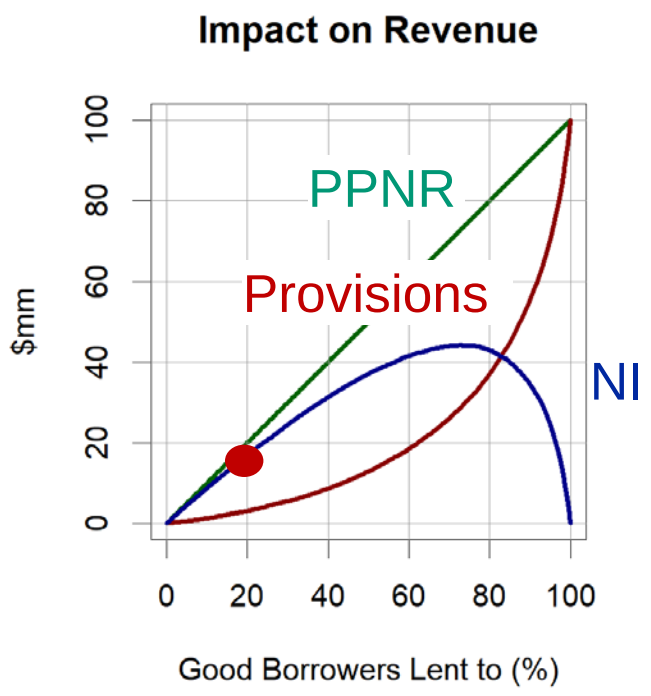
A bank that lends to everyone has no income:

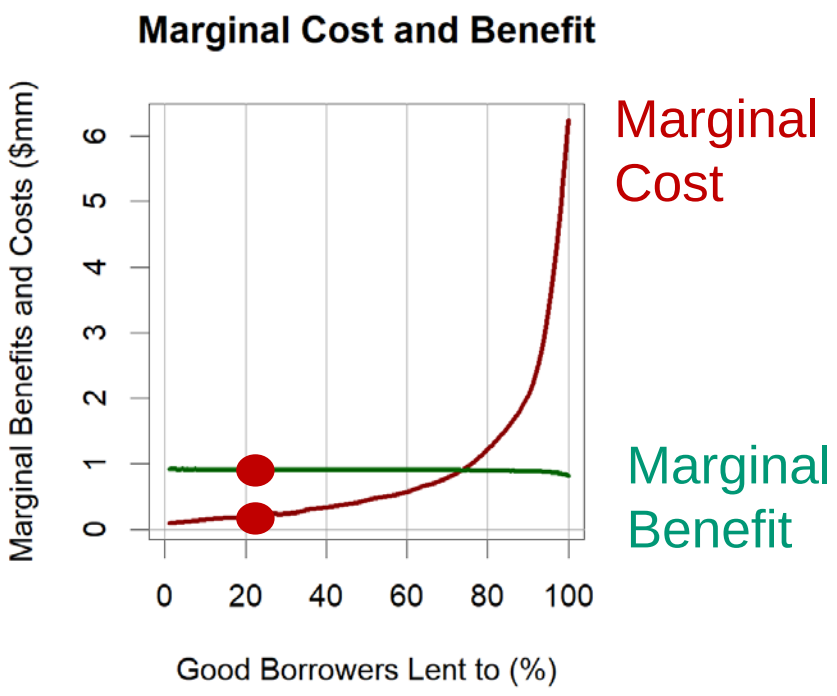
- *Spread = Central Default Tendency*LGD/(1 - Central Default Tendency)*

*PPNR is Pre Provisions Net Revenue

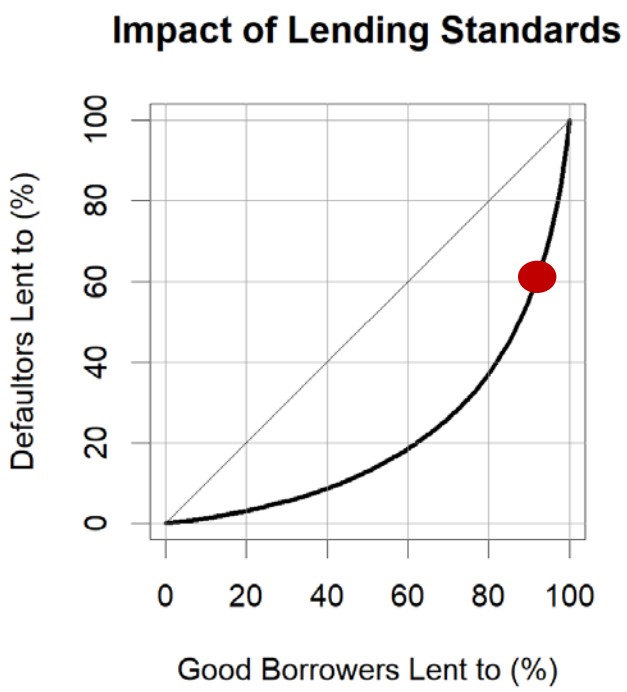
Tighter lending standards result in low provisions, but low PPNR

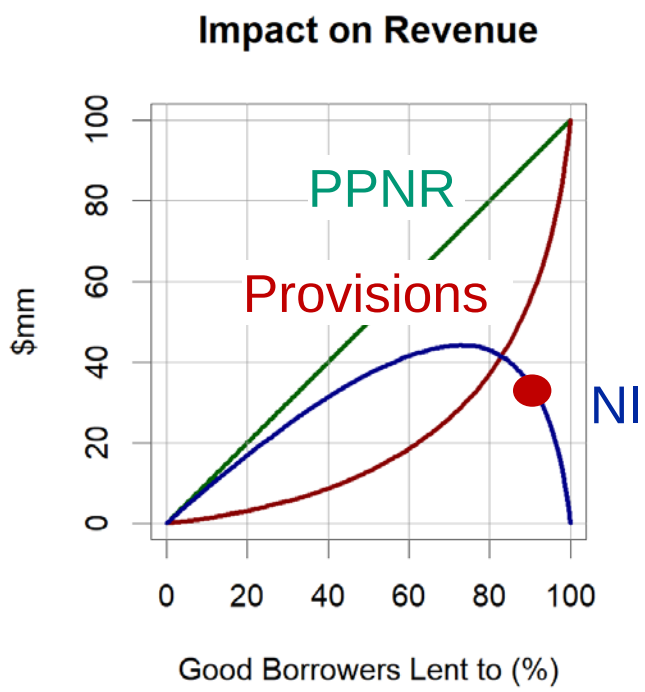


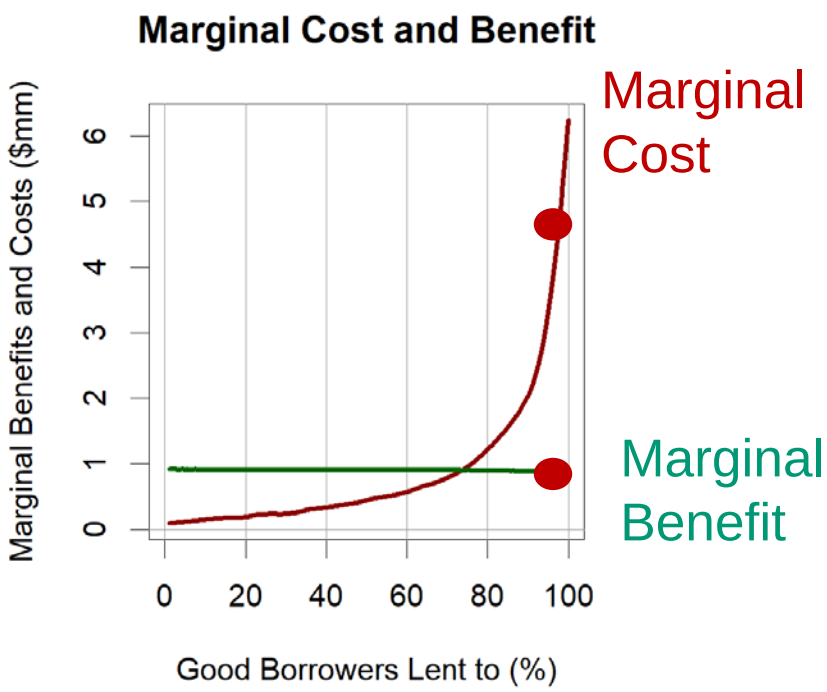




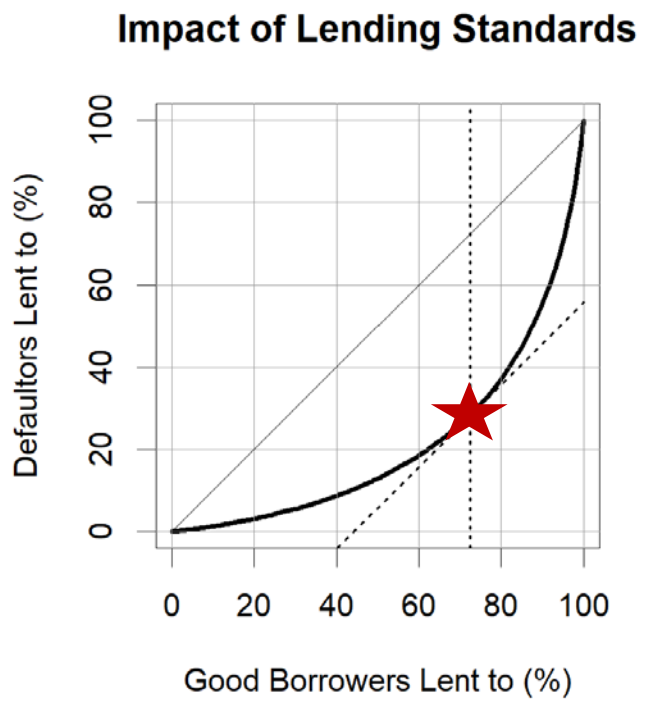
Loose lending standards result in large PPNR, but large provisions as well

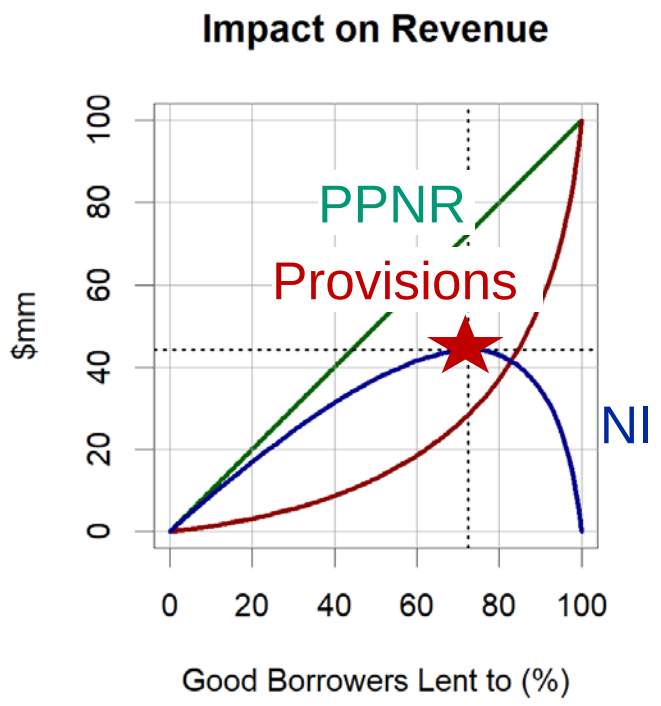


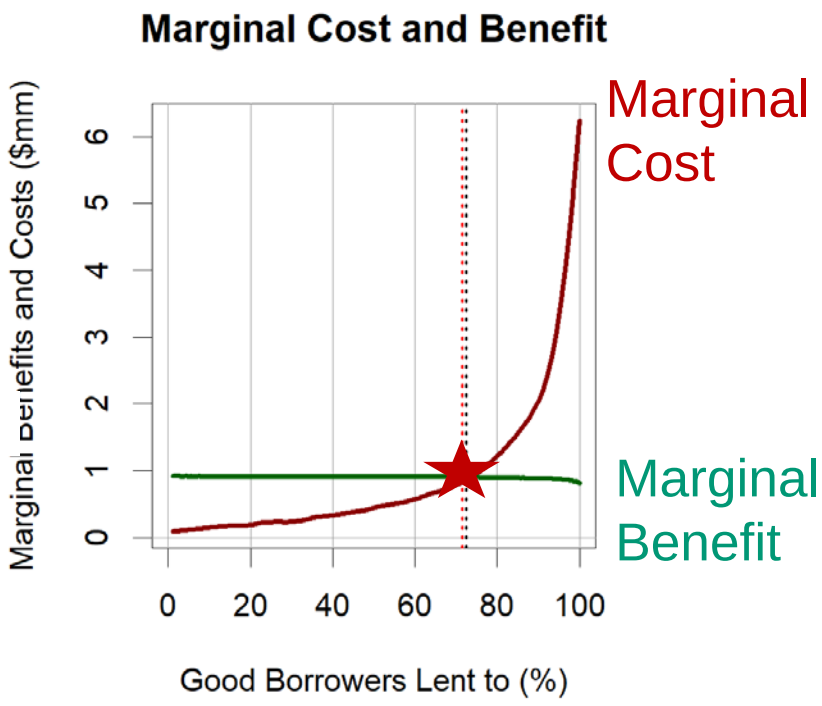




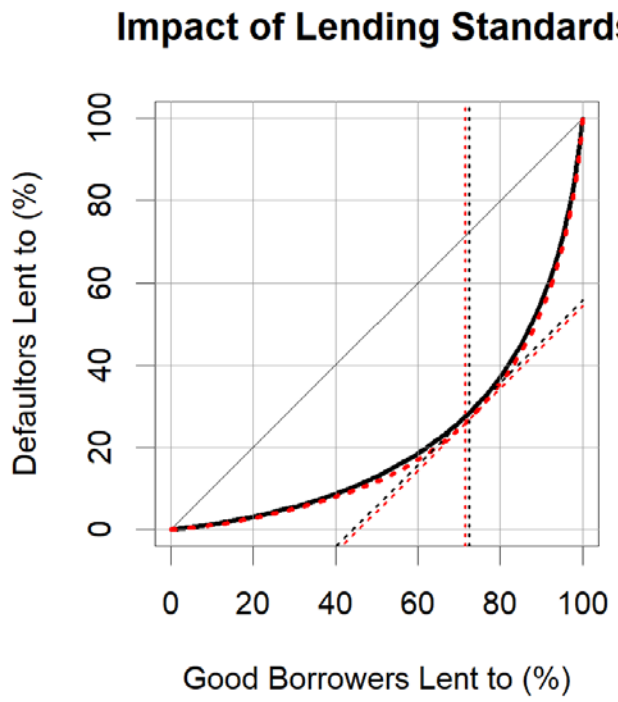
Setting marginal cost to marginal benefit optimizes net income

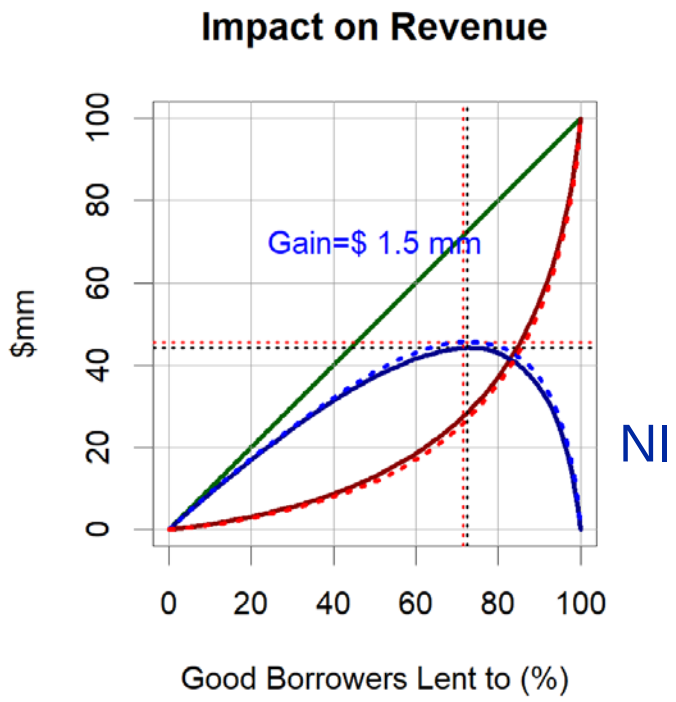


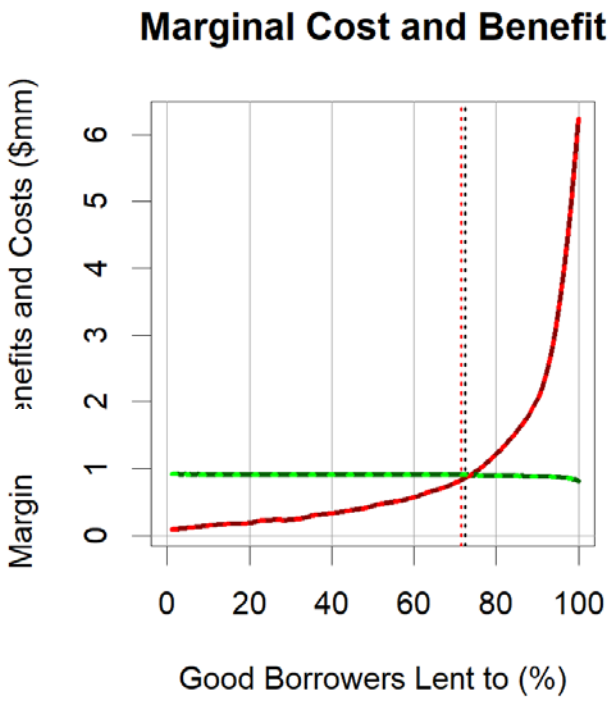




New model yields better cost curves worth $1.5mm







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

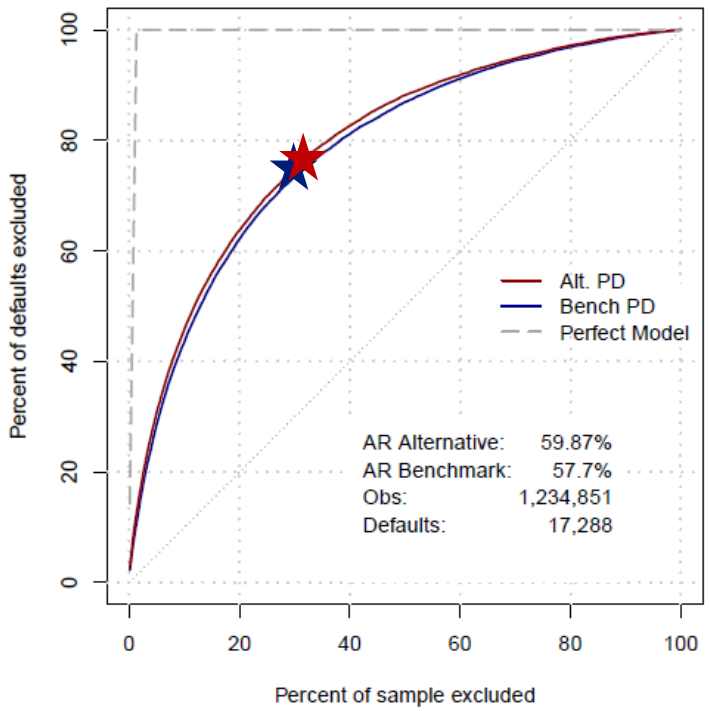


Figure 2: Cap Plot

	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 t “bad” borrowers and only 1.4% more of “good” borrowers.

8

Conclusion

Conclusion

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- 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

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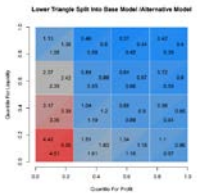
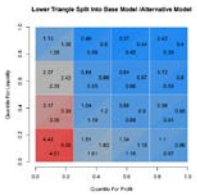
Risk Driver 1

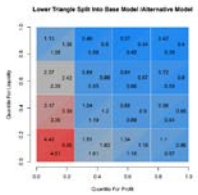
Risk Driver 2

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