Internal Credit Rating methodologies

How they could make a bank more profitable?

May, 2017

In a nut-shell

An Internal Credit Rating methodology …

- .. uses default risk relevant "risk drivers",
  - Quantitative risk drivers (e.g. financial ratios)
  - Qualitative risk drivers (e.g. competitive advantage)
- … combines them appropriately into a credit score
  - e.g. linear combination

How to select the relevant drivers and determine their relative importance?

- … in order to maximise discriminatory power
  - i.e. to rank counterparties from Best to Worst
    such that the better the rank
    the less likely the default would seem to be

How to measure discriminatory power?

… after calibration …

- … and assigns each counterparty a probability of default.
  - i.e. quantify how likely default is expected to be

How to calibrate?

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From Ordinal (Score) to Cardinal (PD) scale

PD buckets define homogenous portfolios or rating classes

CP ID	Score
ID 5	1
ID 19	2
ID 3	3
ID 26	4
ID 8	5
ID 11	6
ID 2	7
ID 40	8
ID 64	9
...	...

Calibration

Score	PD
1	0.020%
2	0.021%
3	0.022%
4	0.024%
5	0.027%
6	0.031%
7	0.037%
8	0.050%
9	0.069%
...	...

Bank's MasterScale

PD	Rating
0.020%	C01
0.021%	C02
0.022%	C02
0.024%	C02
0.027%	C02
0.031%	C02
0.037%	C02
0.050%	C02
0.069%	C03
...	...

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Hypothetical portfolio of bank clients (Part I)

Rating	Mid-Point PD	Counts	Expected Number of Defaults	MIN Number of Defaults	Realized Number of Defaults	MAX Number of Defaults
1	0.01%	**1'000**	0	-	**-**	1
2	0.04%	**1'000**	0	-	**-**	2
3	0.09%	**1'000**	1	-	**-**	4
4	0.18%	**1'000**	2	-	**-**	6
5	0.36%	**1'000**	4	-	**2**	9
6	0.60%	**1'000**	6	1	**5**	12
7	0.84%	**1'000**	8	3	**12**	16
8	1.08%	**1'000**	11	4	**5**	19
9	1.80%	**1'000**	18	9	**5**	28
10	3.00%	**1'000**	30	18	**5**	43
11	4.20%	**1'000**	42	28	**12**	57
12	5.04%	**1'000**	50	35	**1**	67
13	8.00%	**1'000**	80	61		101
14	13.00%	**1'000**	130	106		155
15	40.00%	**-**	-	-		-
Totals		**14'000**	**382**	**265**	**47**	**520**
			2.73%	**1.89%**	**0.34%**	**3.71%**

- Too conservative in a good year? (using just CRITBINOM in Excel as a test)
- Need to re-address the "How" questions (evidence of some mis-ranking):
  - Expected discriminatory power of 66.48% (with confidence bounds of 60% and 73%)
  - Realized discriminatory power of 24.31% is significantly lower than expected

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Hypothetical portfolio of bank clients (Part Ia)

		Basel II implied probabilities							
		15.87%	68.27%	15.87%					
Rating	Mid-Point PD	PD conditional on High Systematic Risk	PD conditional on Medium Systematic Risk	PD conditional on Low Systematic Risk	Counts	Expected Number of Defaults	MIN Number of Defaults	Realized Number of Defaults	MAX Number of Defaults
1	0.01%	0.05%	0.00%	0.00003%	1'000	0	-	-	-
2	0.04%	0.20%	0.01%	0.00021%	1'000	0	-	-	-
3	0.09%	0.44%	0.03%	0.00077%	1'000	0	-	-	-
4	0.18%	0.82%	0.07%	0.00239%	1'000	0	-	-	1
5	0.36%	1.53%	0.17%	0.00792%	1'000	0	-	2	1
6	0.60%	2.38%	0.32%	0.02%	1'000	0	-	5	2
7	0.84%	3.14%	0.49%	0.04%	1'000	0	-	12	2
8	1.08%	3.85%	0.67%	0.06%	1'000	1	-	5	3
9	1.80%	5.72%	1.27%	0.16%	1'000	2	-	5	5
10	3.00%	8.39%	2.34%	0.43%	1'000	4	-	5	10
11	4.20%	10.82%	3.46%	0.76%	1'000	8	2	12	15
12	5.04%	12.44%	4.25%	1.02%	1'000	10	4	1	18
13	8.00%	17.92%	7.08%	2.05%	1'000	20	11		32
14	13.00%	26.46%	11.95%	4.07%	1'000	41	27		56
15	40.00%	61.35%	39.56%	20.55%	-	-	-		-
Totals		6.73%	2.29%	0.62%	14'000	86	44	47	145
						0.62%	0.31%	0.34%	1.04%

- This slide is a follow-up on comments by seminar participants – what does “Too conservative in a good year” mean?
- For ratings highlighted in red the conservative binomial test says **NO**, i.e. if we knew in advance that the year would turn out to be good, we would use the probabilities of default that condition on low systematic risk and ultimately would have been "too optimistic" for the names allocated to homogenous portfolios with ratings 5 to 8. As we do not know in advance, we have to average the values of the tree additional columns (with the relative weights of Basel II) and use the result (shown in the column labeled "Mid-Point PD") as done above.

How to select relevant risk drivers? (Part I)

Check past performance

Financials

Non-Financials

Behavior Factors

Possible risk drivers

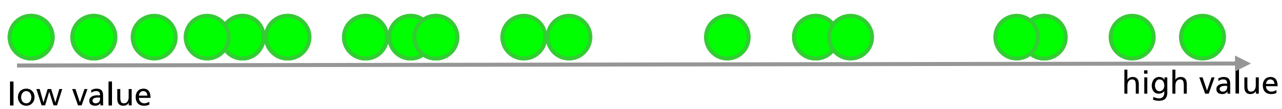
Financial risk driver a: Gearing

Financial risk driver b: Return on equity

Financial risk driver c: Liquidity

sort counterparts
according to the value of the risk driver

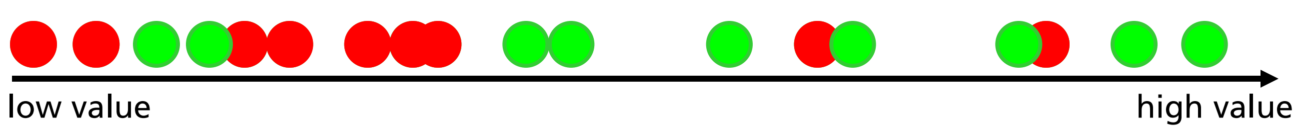
Year 1:



After one year
some obligors
defaulted, some not

performing   defaulted

Year 2:



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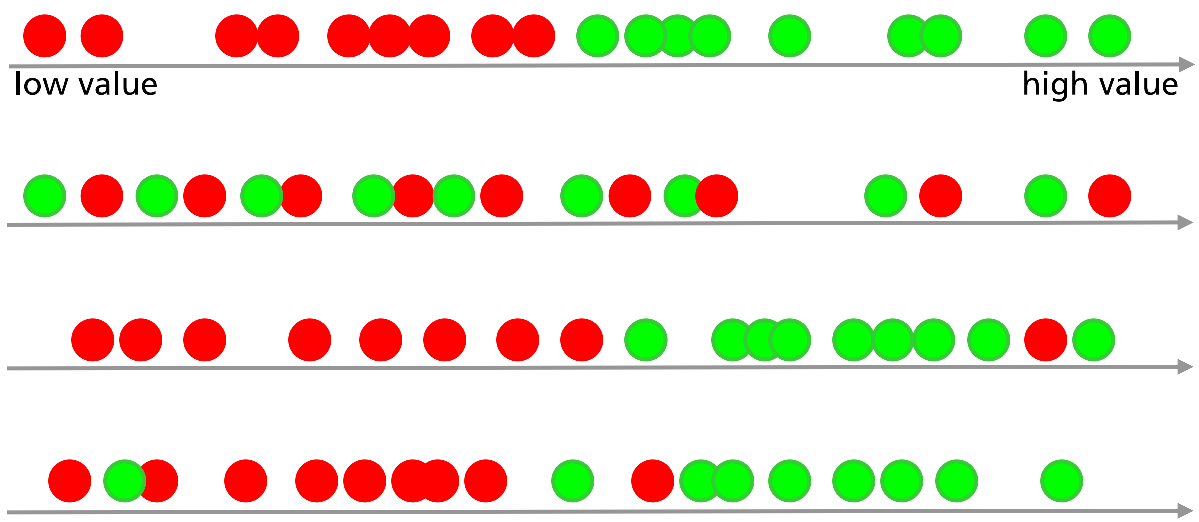
How to select relevant risk drivers? (Part II)

Assess discriminatory power

Possible outcomes for a given risk driver

Discriminatory power



100%

0% (coin tossing)

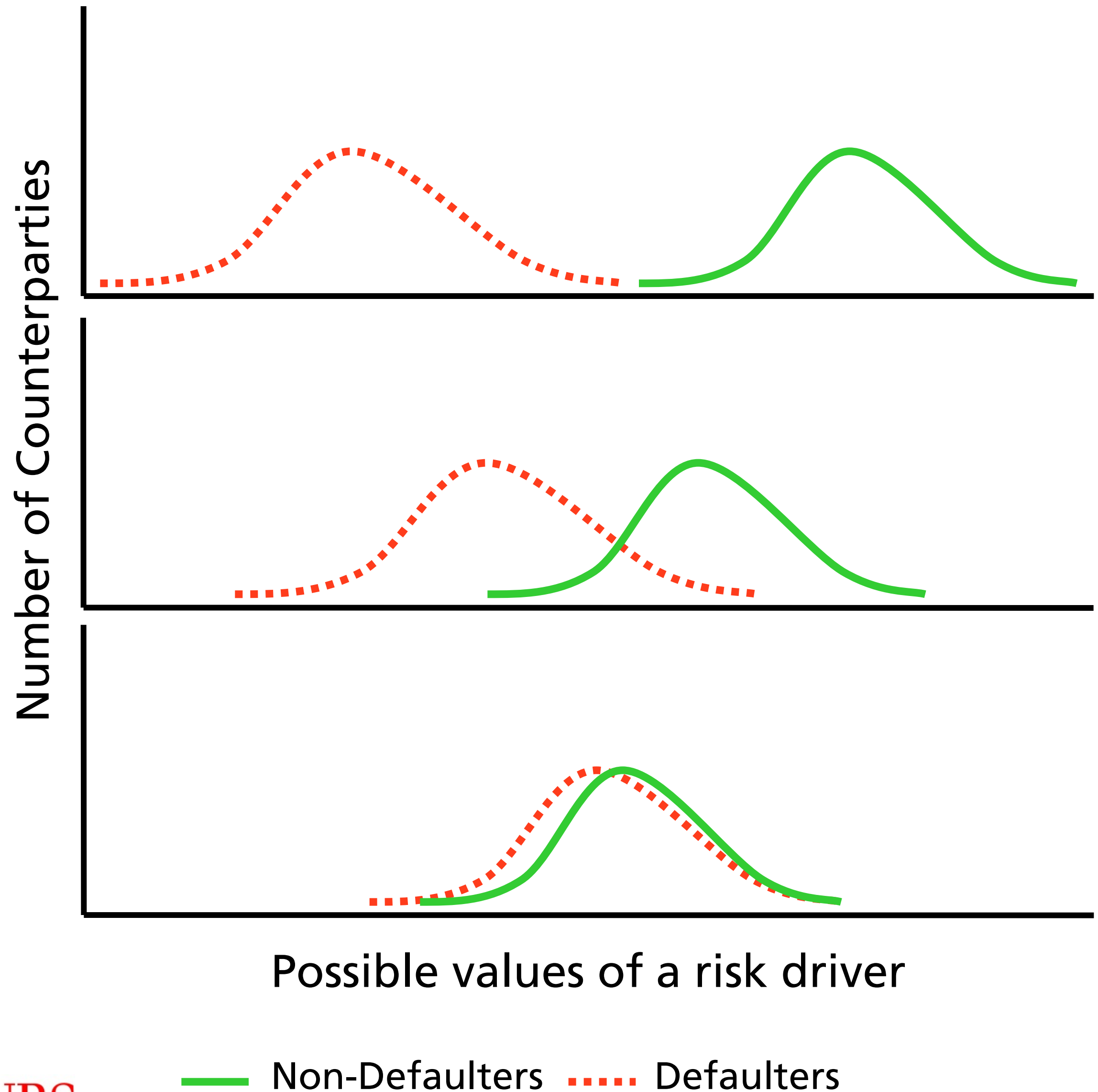
80%

80%

Note: Different rank orderings may have the same discriminatory power, but very different business implications.

How to measure discriminatory power (Part I)

When a value becomes a symptom?



Discrimination	Measure
Perfect	100
Good	50
Poor	0

How to measure discriminatory power (Part II)

5 x (green)
5 x (red)

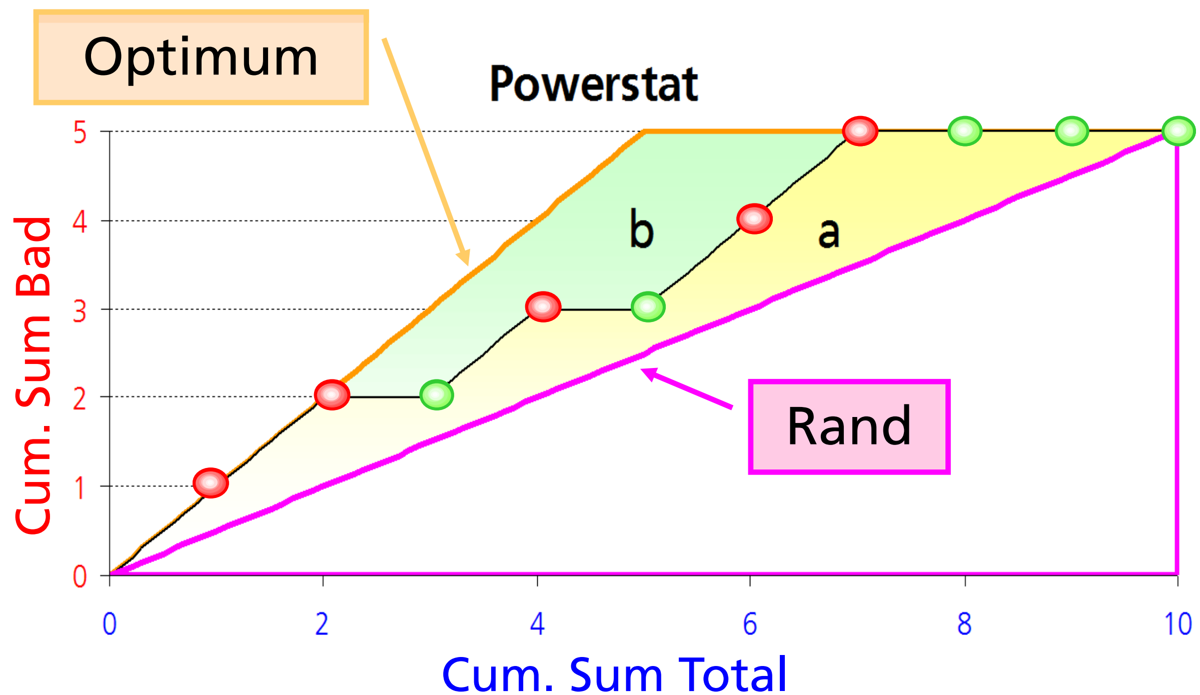
Bad Sorted by Score *good*

Total	1	2	3	4	5	6	7	8	9	10
Bad	1	2	2	3	3	4	5	5	5	5

a = model at hand

a + b = perfect model

$$\text{Accuracy ratio} = \frac{a}{a+b}$$



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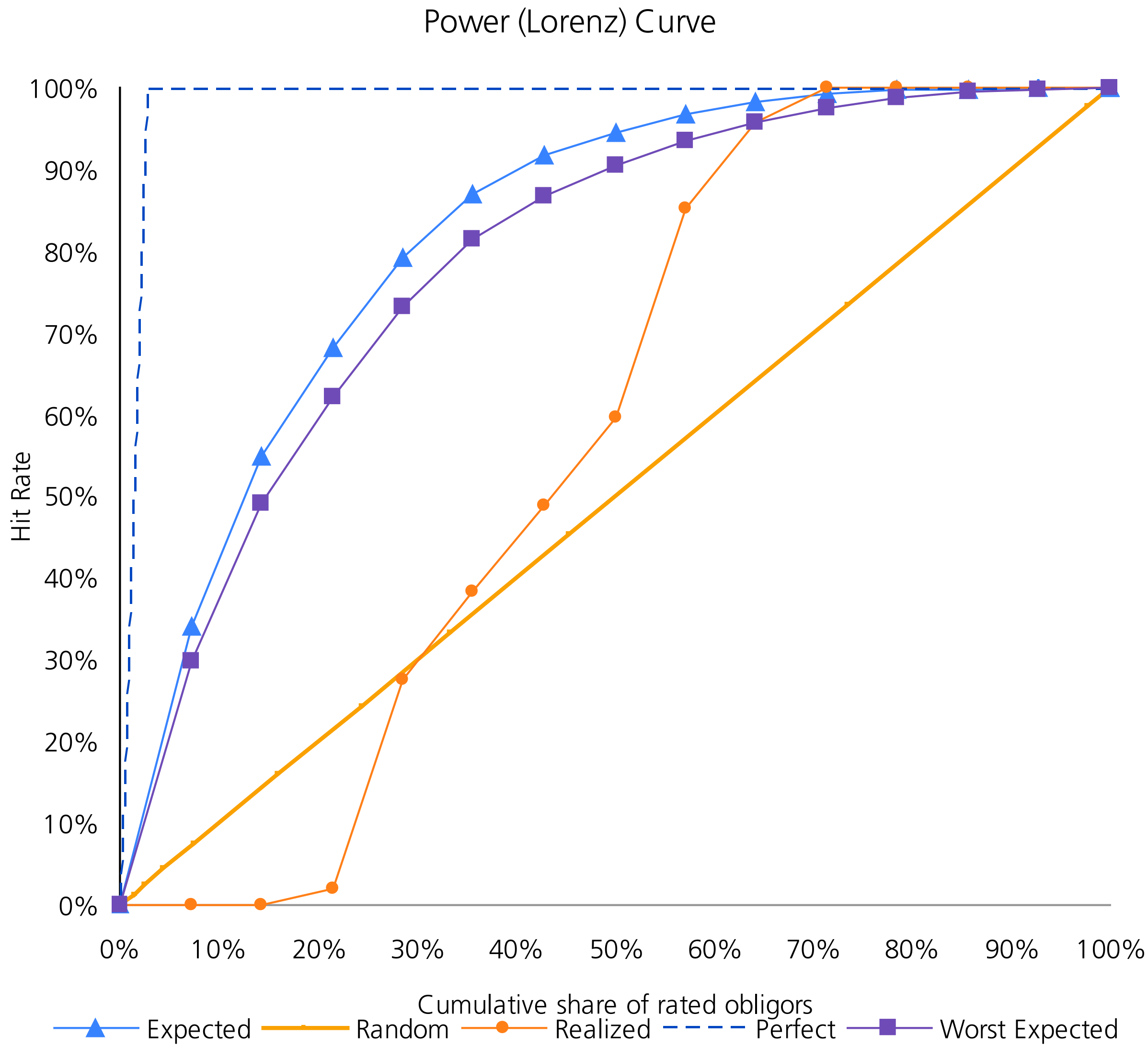
Hypothetical portfolio of bank clients (Part II)

Visualizing discriminatory power



- "Expected" discriminatory power of 66.48%
- "Best Expected" discriminatory power of 73.49% (not plotted)
- "Worst Expected" discriminatory power of 66.48%
- Realized discriminatory power is expected to be "above" or "between" the curves of "Expected" and "Worst Expected"

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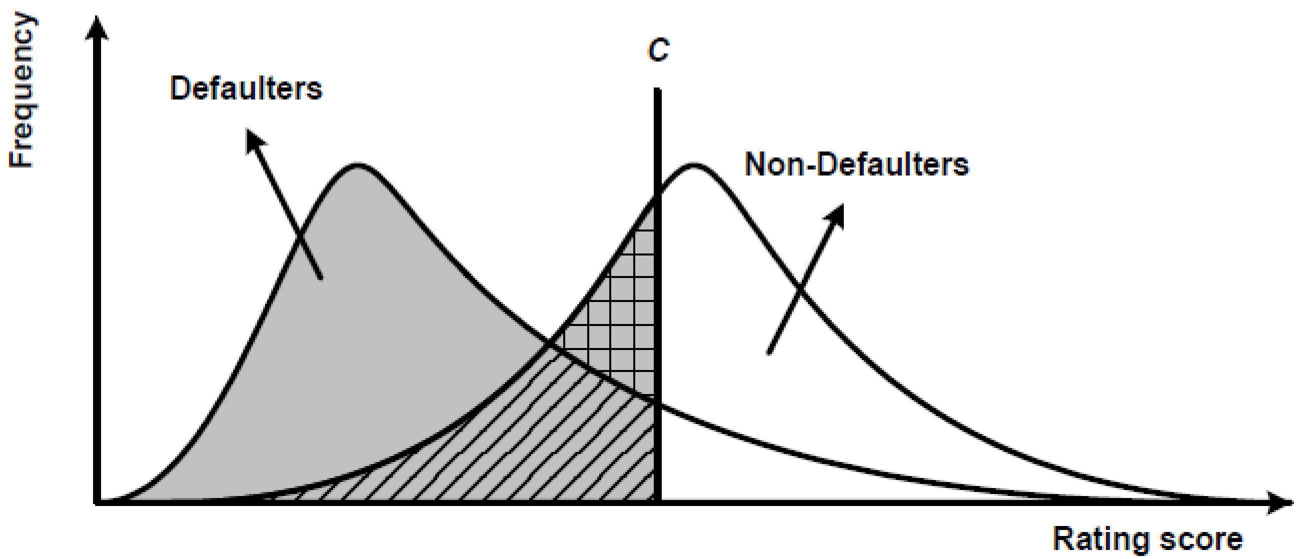
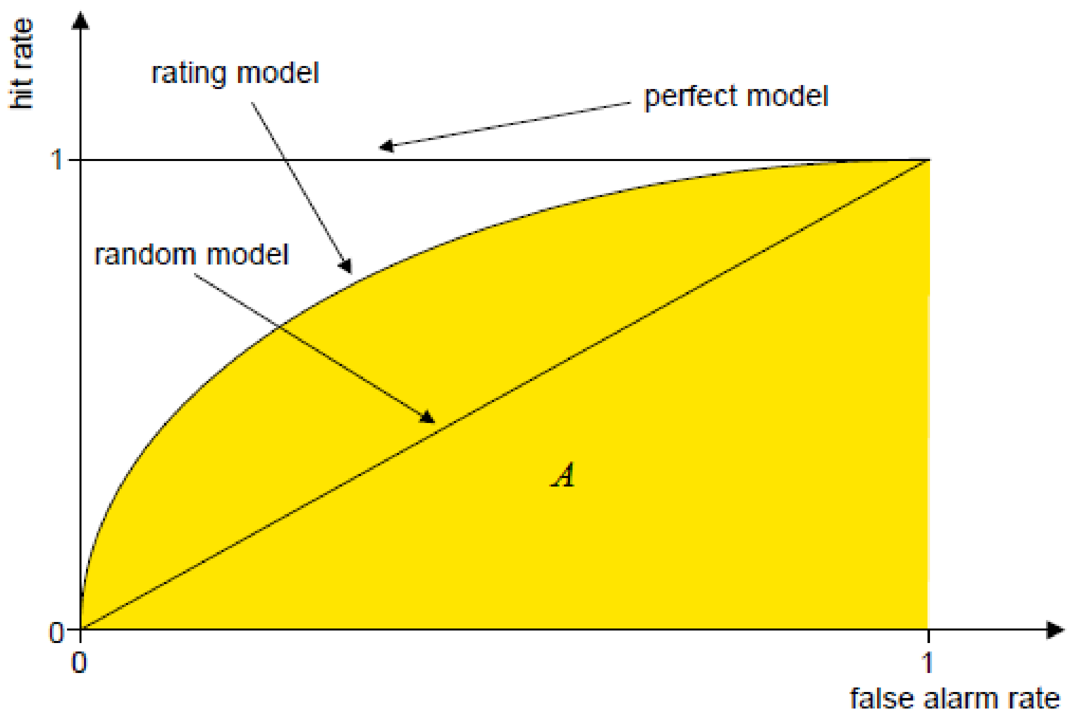
Receiver operating characteristic

- Assume someone has to find out from the rating scores which debtors will survive during the next period and which debtors will default
- We define the hit rate $HR(c) = \dfrac{H(c)}{N_D}$
  where H(c) is the number of defaulters classified correctly,
- We define false alarm rate $FAR(c) = \dfrac{F(c)}{N_{ND}}$
  where *F(C)* is the number of false alarms, i.e. the number of non-defaulters that were classified incorrectly as defaulters



Receiver operating characteristics

- The ROC curve is constructed as follows. For all cut-off values *C* that are contained in the range of the rating scores the quantities *HR(C)* and *FAR(C)* are computed.
- The ROC curve is a plot of *HR(C)* versus *FAR(C)*.



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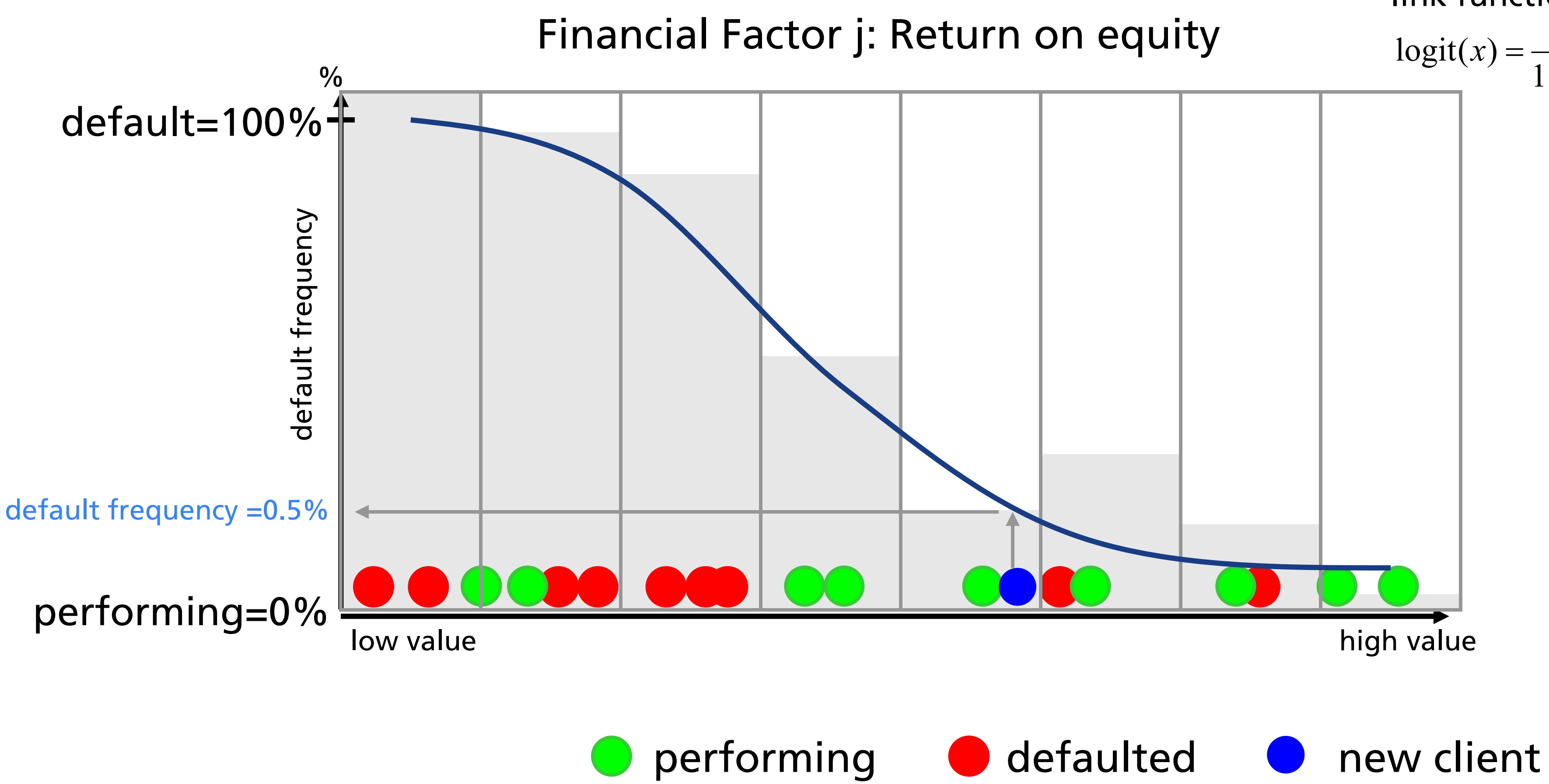
How to calibrate

From rank ordering to probability of default

Calibration is based on logit link function:

$$\text{logit}(x) = \frac{1}{1+\exp(\alpha x + \beta)}$$



The calibrated link function (fixed parameters) defines the relation between score (ratio) and default frequency (probability of default).

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How it all relates to profits (Part I)

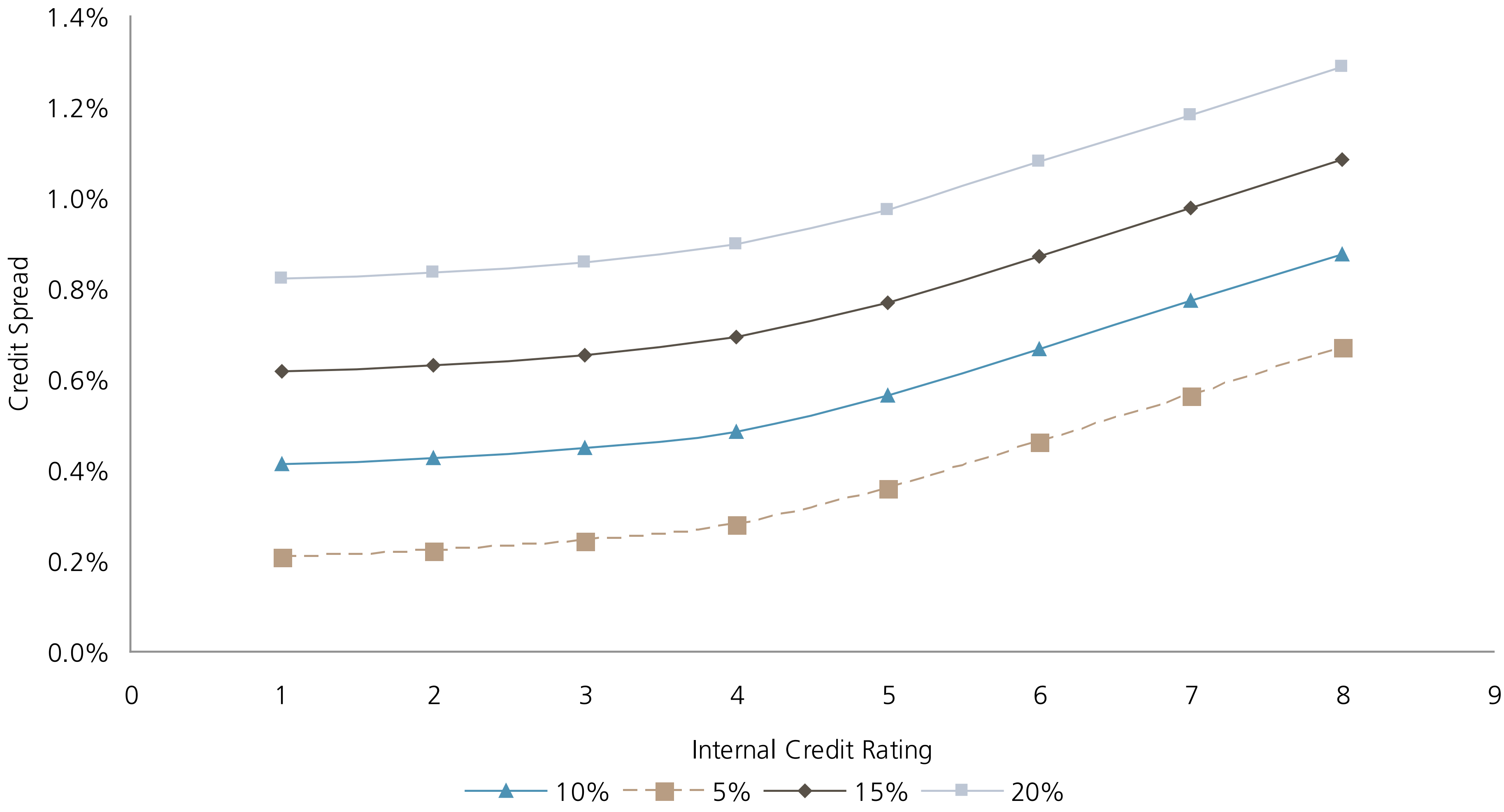
Assume simple one year contract

$$NPV = -1CHF + \frac{1}{1+\delta}\left(PD \times (1 - LGD) \times 1CHF + (1 - PD) \times 1CHF \times (1 + \delta + s)\right)$$

- If a bank has:
  - required return on equity of 10%
  - leverage ratio of 4%
  - cost of debt (or deposit rate) of 2%
- Then every 1 CHF lent out is 4 cents equity and 96 cents debt
- So the required NPV is 40 bps
- And the relevant discount rate (delta) is 2.32%
- How do spreads per rating look like, if we fix LGD to 40%?

How it all relates to profits (Part II)

Spreads increase in rating and in required return on equity



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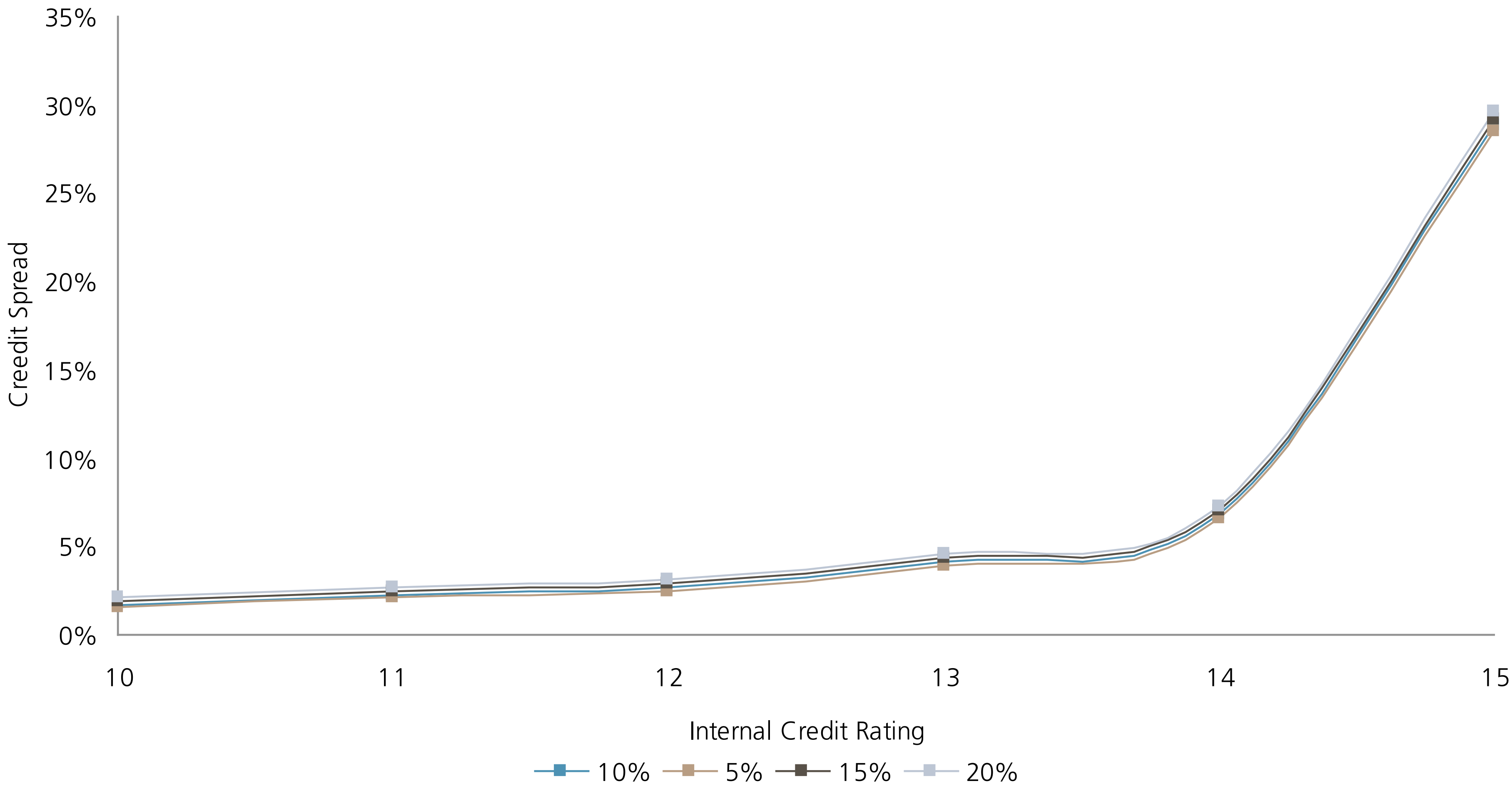
How it all relates to profits (Part IIa)

Spreads increase dramatically for sub-investment grades



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How it all relates to competition (Part I)

Demonstrated via "the Game"

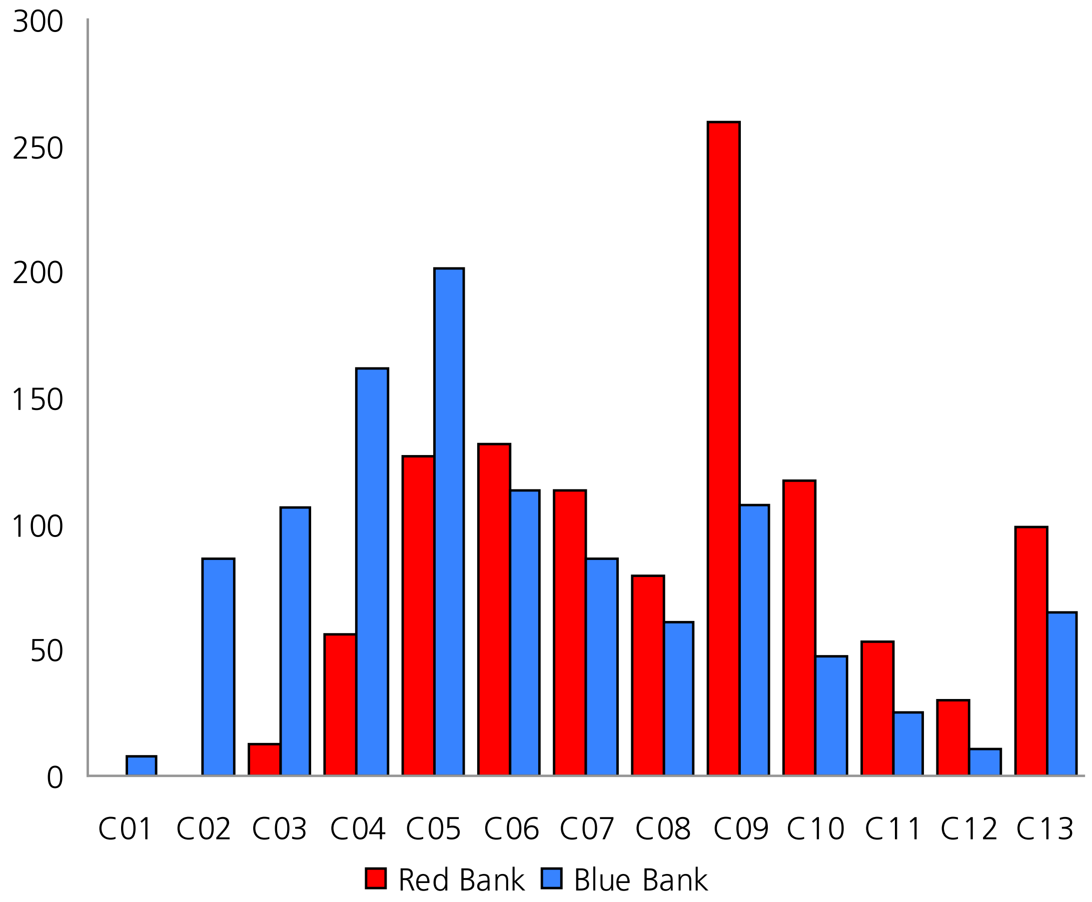
- Two banks compete for market share of a new market
- Both the "Blue Bank" and the "Red Bank" have two types of experts:
  - Quantitatively minded experts with strong statistical background
  - Non-Quantitatively minded experts with a lot of practical experience
- Both banks have the same required return on equity and leverage level
- A benevolent government and a principles-based regulator provide selected information about a relatively stable market:
  - One-year loans only
  - 10 years of default history
  - 11 key criteria kindly collected by the local regulator and made available to both banks
  - 2.5% cap on the maximum spread that can be charged in addition to the 2% ref. rate

How it all relates to competition (Part II)

The rules of "the Game"

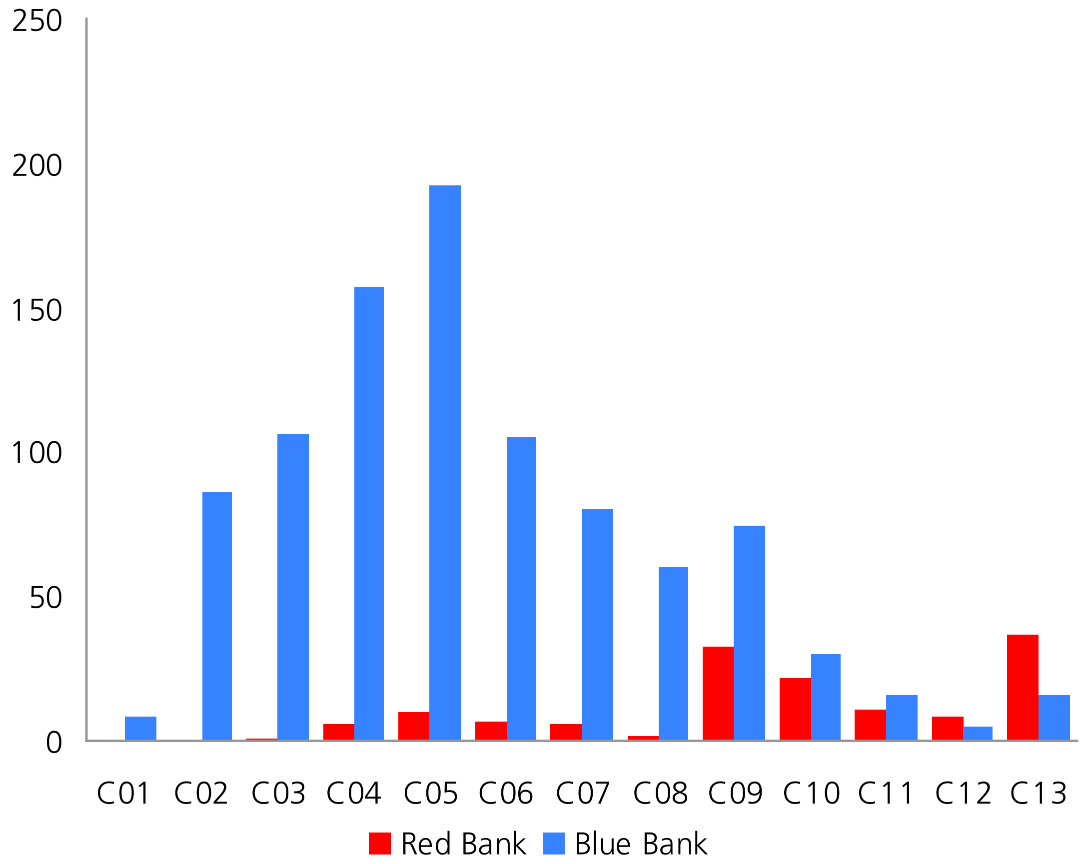
- Within each bank the two types of experts have to come up with one rating tool and communicate to the regulator some key figures
- Between the banks there is a fierce competition for talent, ideas and resources, but both banks use the same master scale
- Advanced IRB status is a prerequisite for any bank to participate in the market
- Once banks enter the market, the market shares are calculated, based on "rating-implied spreads", i.e. clients go to the bank that is cheaper
- One year after entry, the allocation of the realized default rates and discriminatory power is reported

Before entering the market



- Rating distributions if 100% market share was possible
- Discriminatory power of "Red Bank" 51.49% and of "Blue Bank" 92.7%

At market entry



- Market share of "Red Bank" 13.27% and of "Blue Bank" 86.73%

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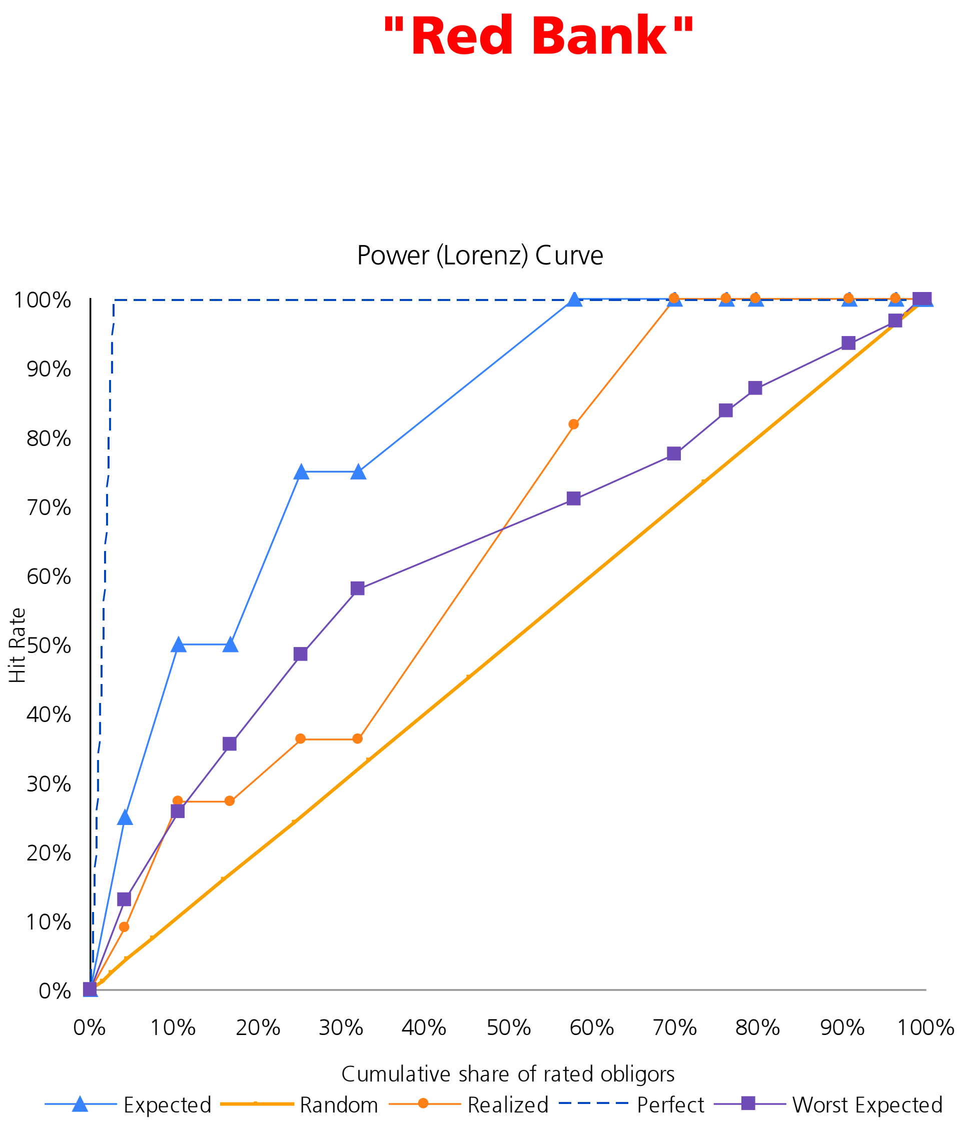
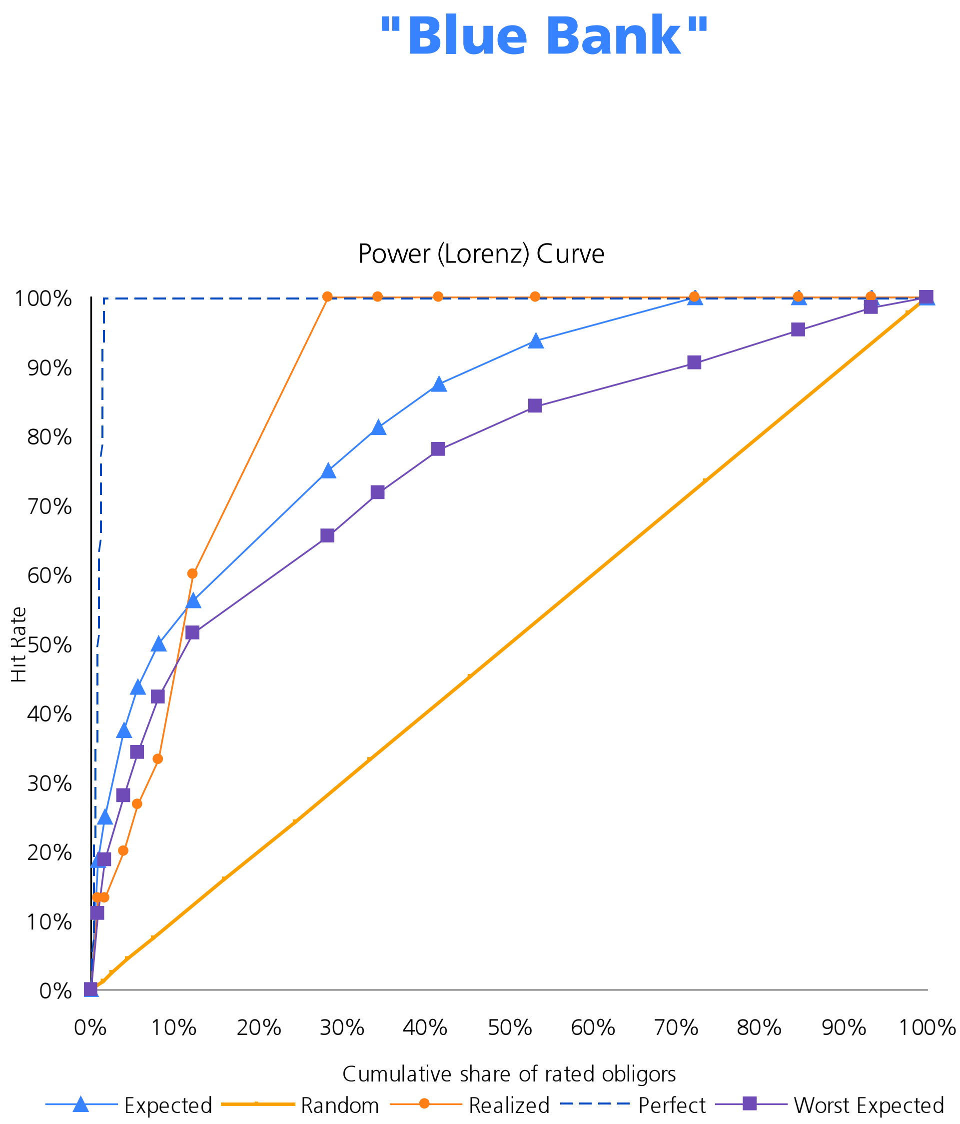
One year after entering the market





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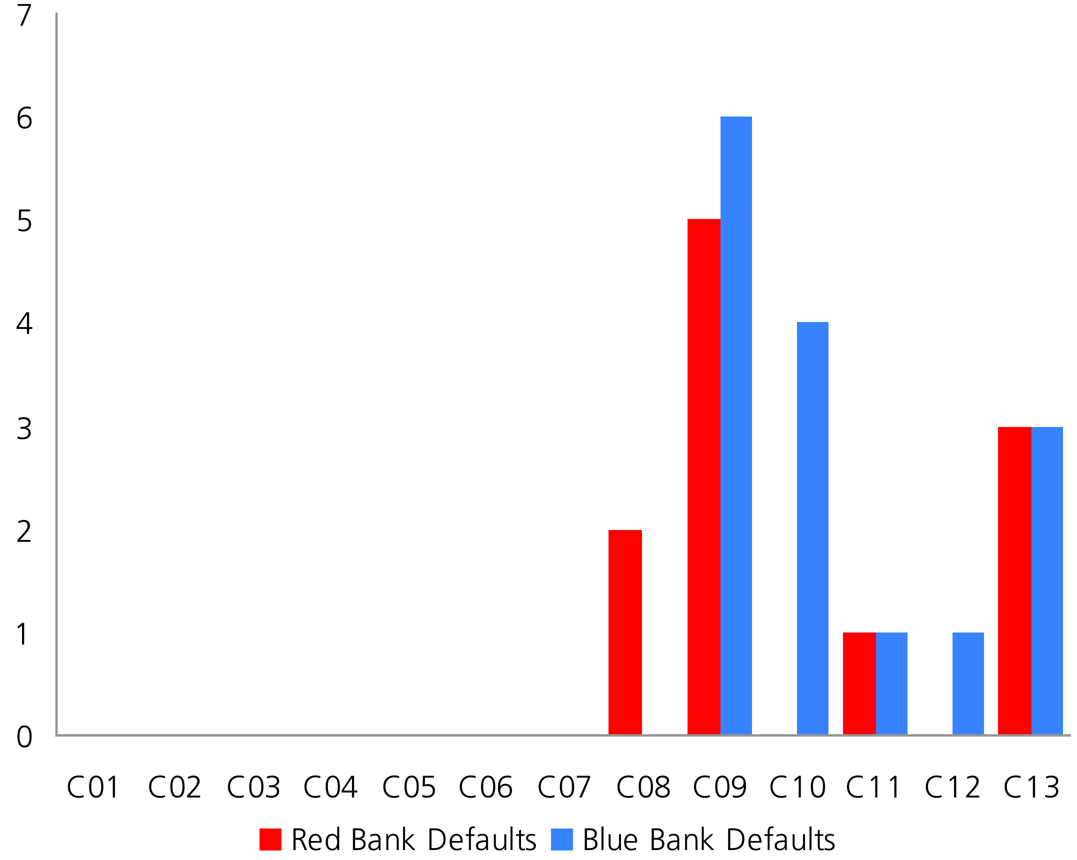
How defaults affected profitability?



- Share of defaulters for "Red Bank" 41.38% and for "Blue Bank" 58.62%
- Realized discriminatory power of "Red Bank" 31% and of "Blue Bank" 78%
- Return on equity of "Red Bank" -14% and of "Blue Bank" 46%

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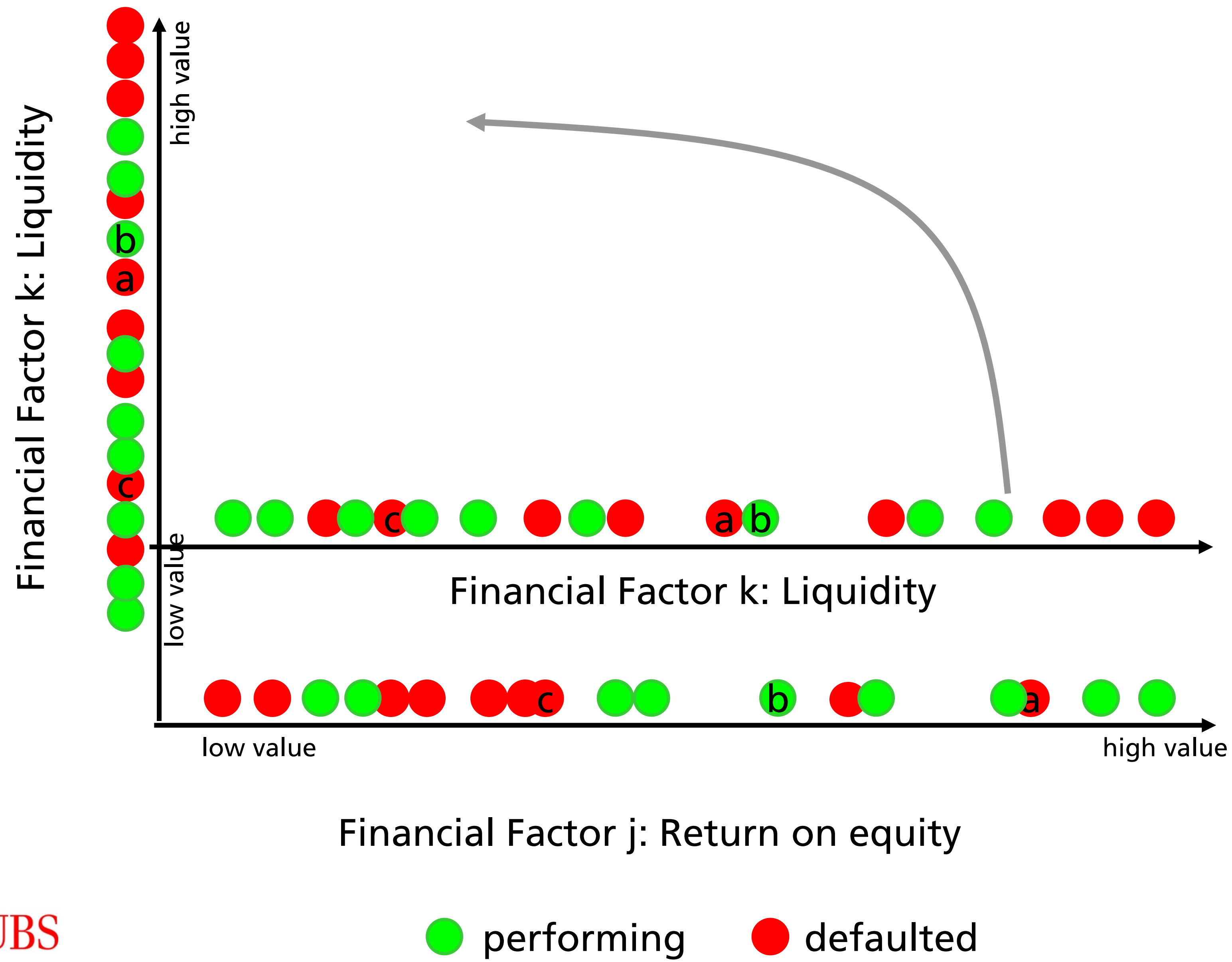
APPENDIX A

The Multivariate Case

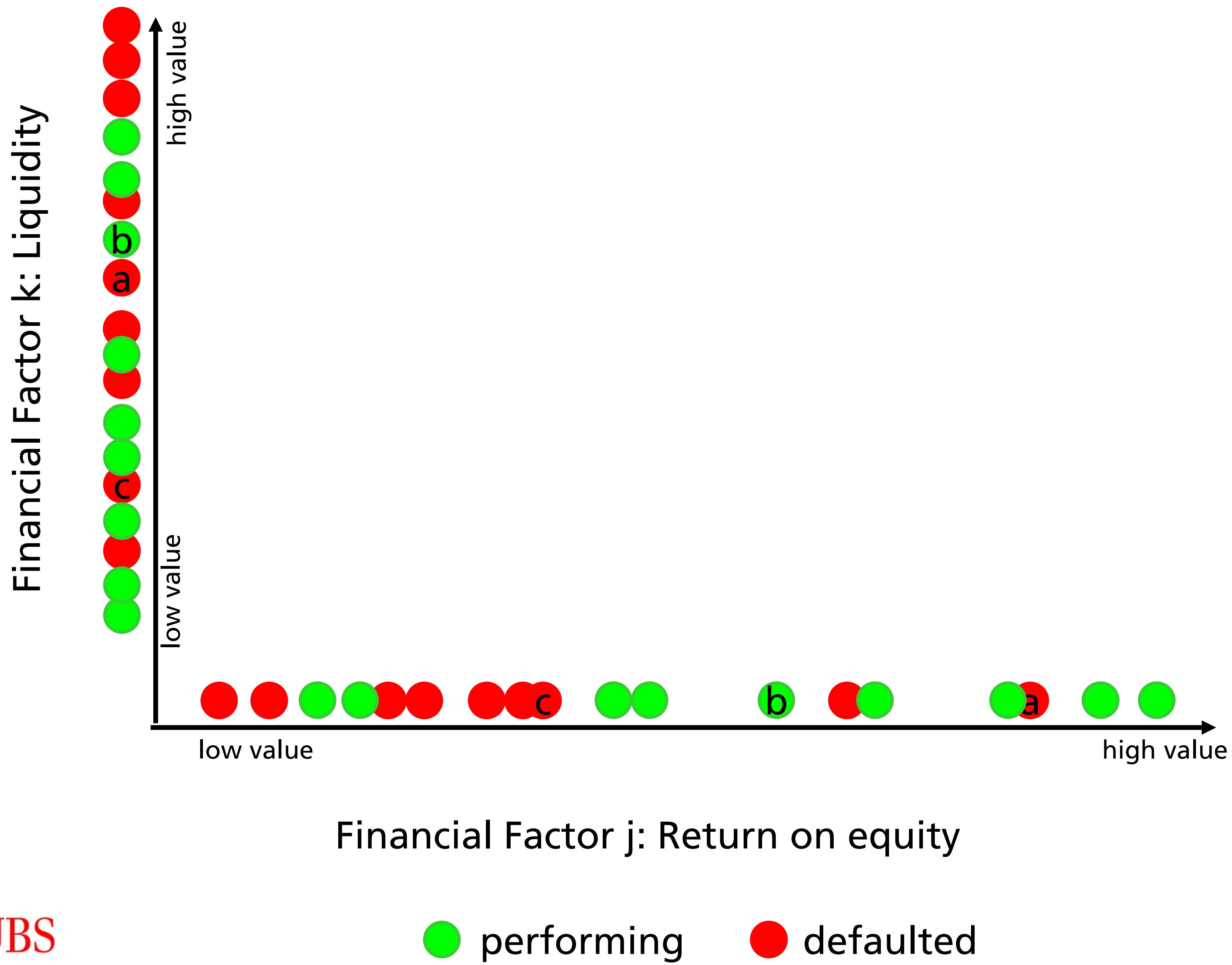
How to incorporate more than one risk driver

The multivariate case: Value added for rank ordering



How to incorporate more than one risk driver

The multivariate case: Value added for rank ordering



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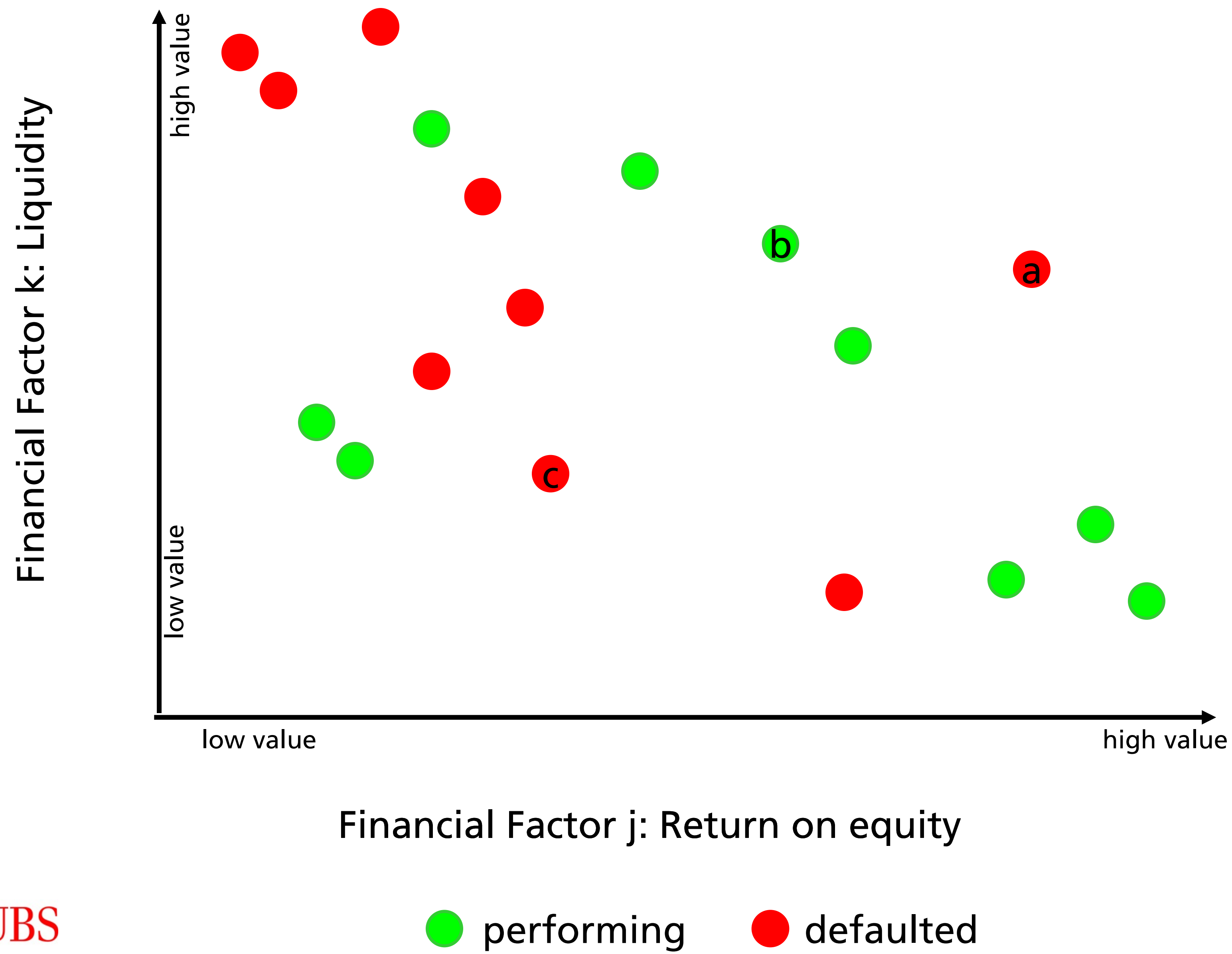
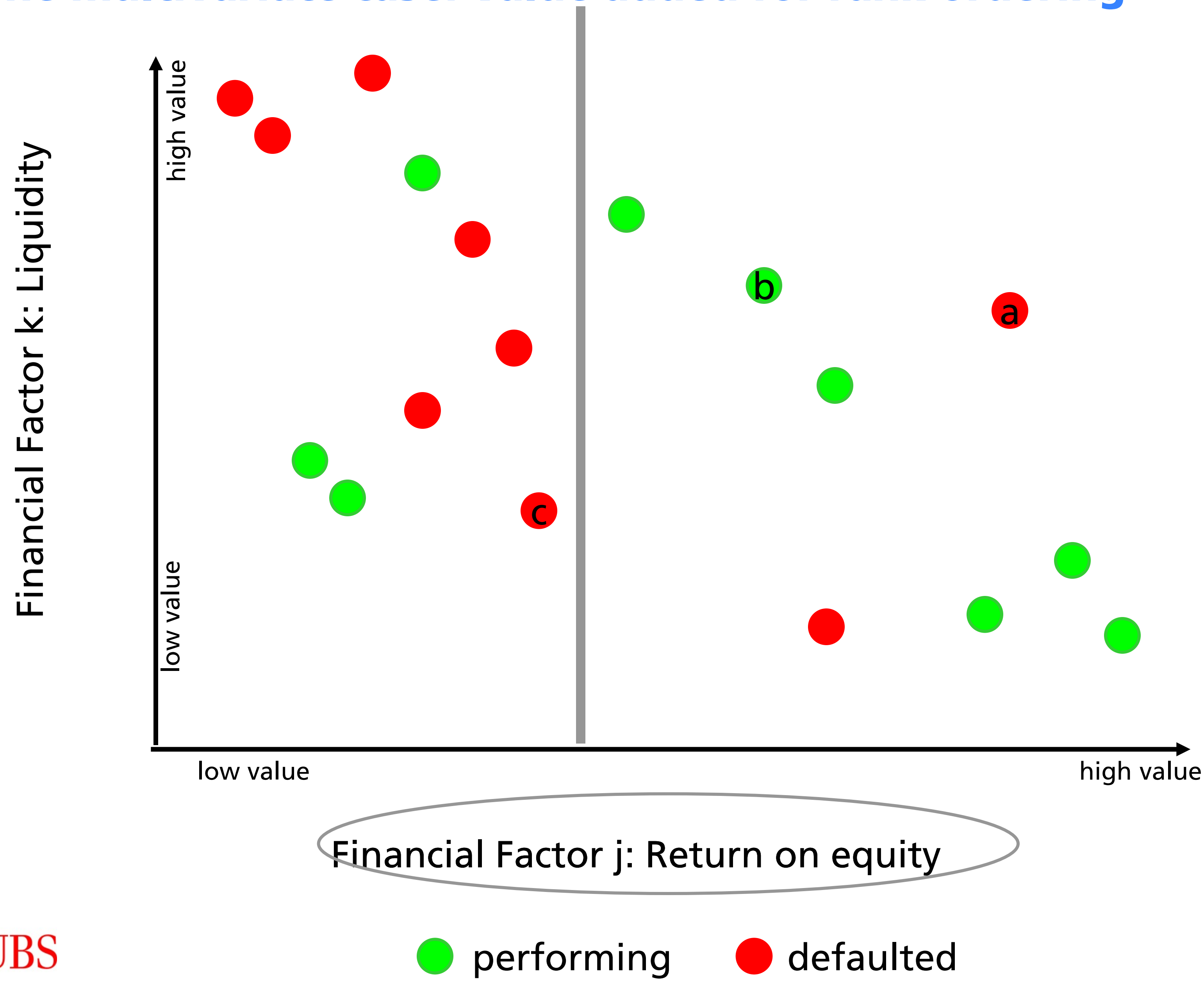
How to incorporate more than one risk driver

The multivariate case: Value added for rank ordering



How to incorporate more than one risk driver

The multivariate case: Value added for rank ordering



How to incorporate more than one risk driver

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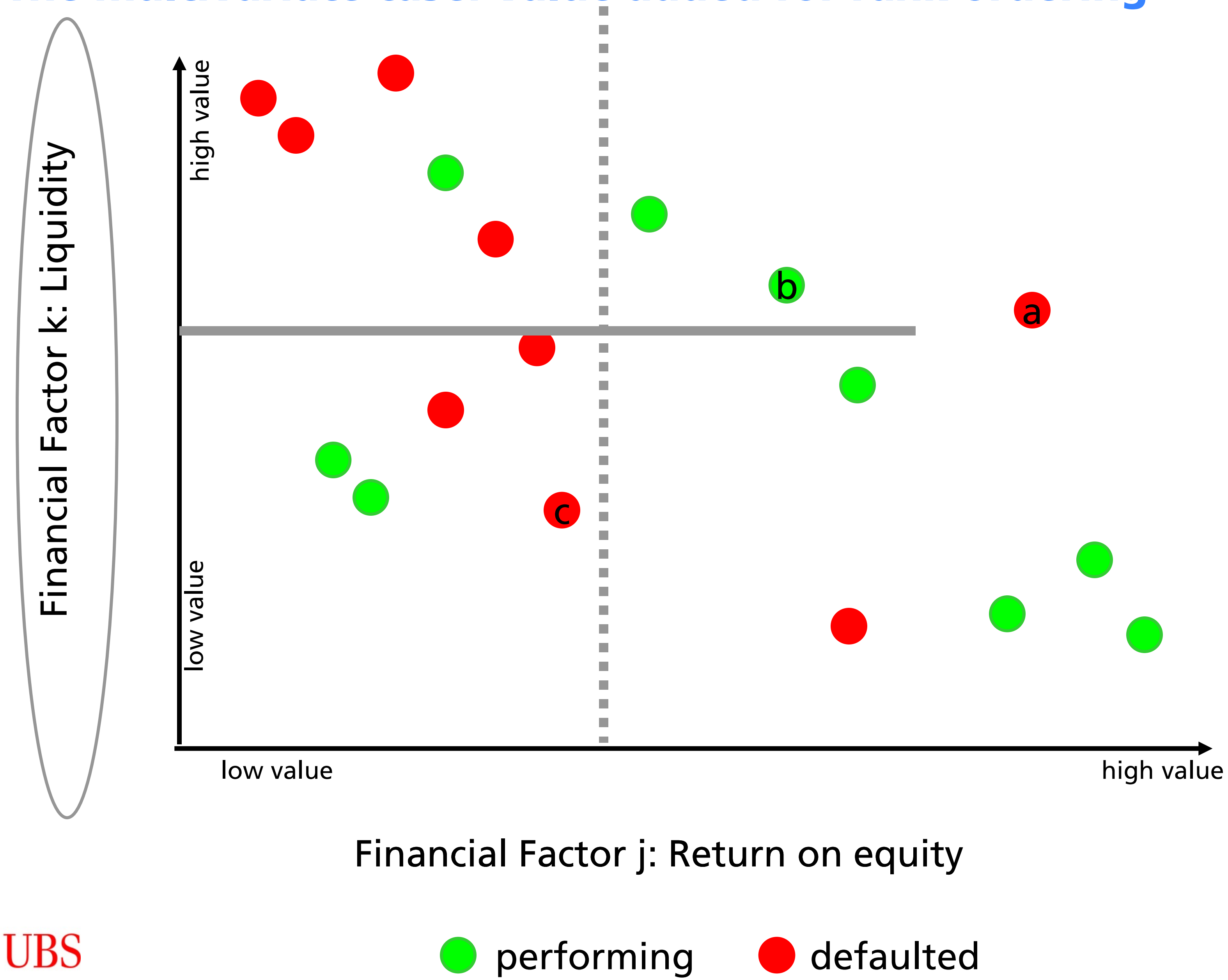

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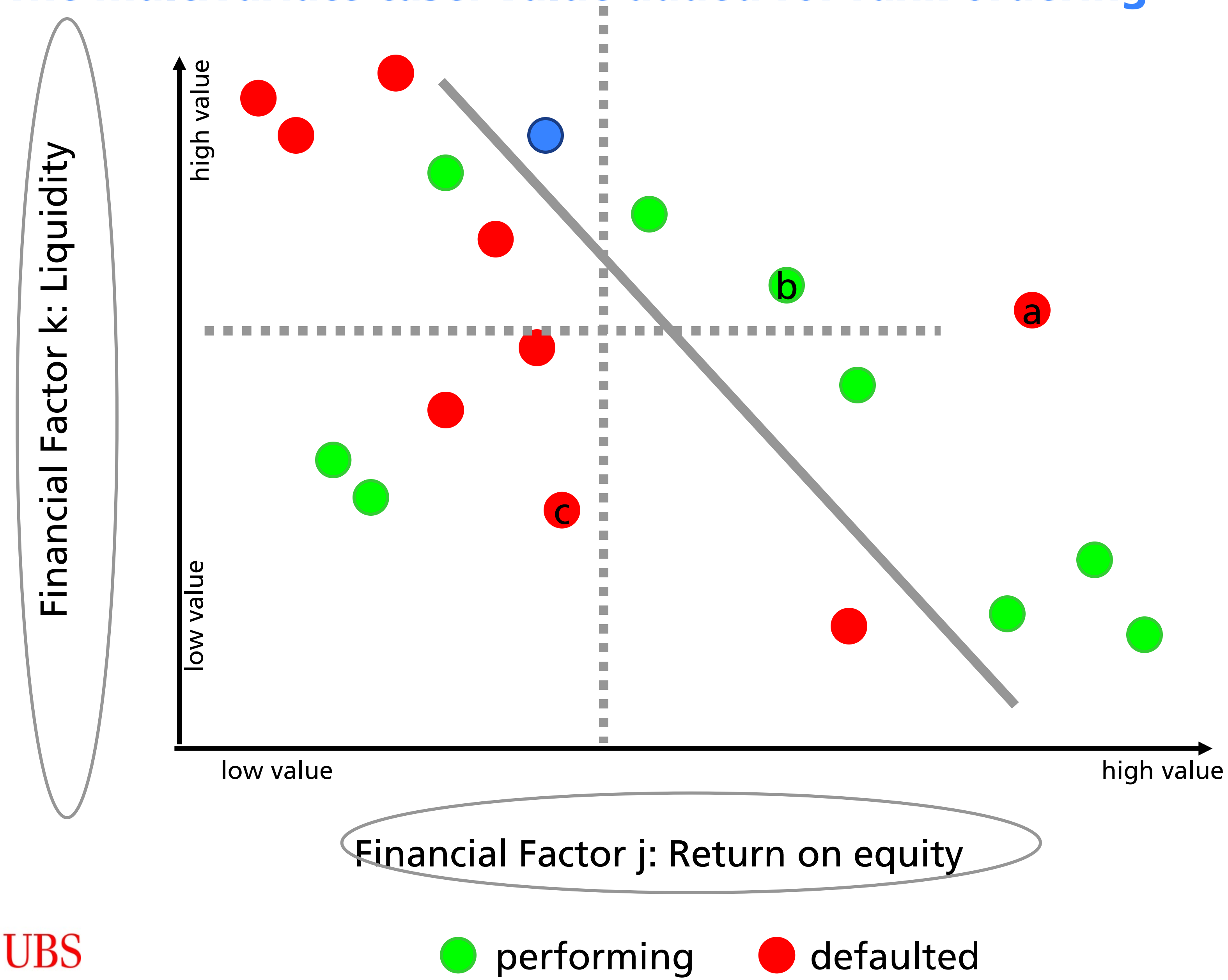
How to incorporate more than one risk driver

The multivariate case: Value added for rank ordering



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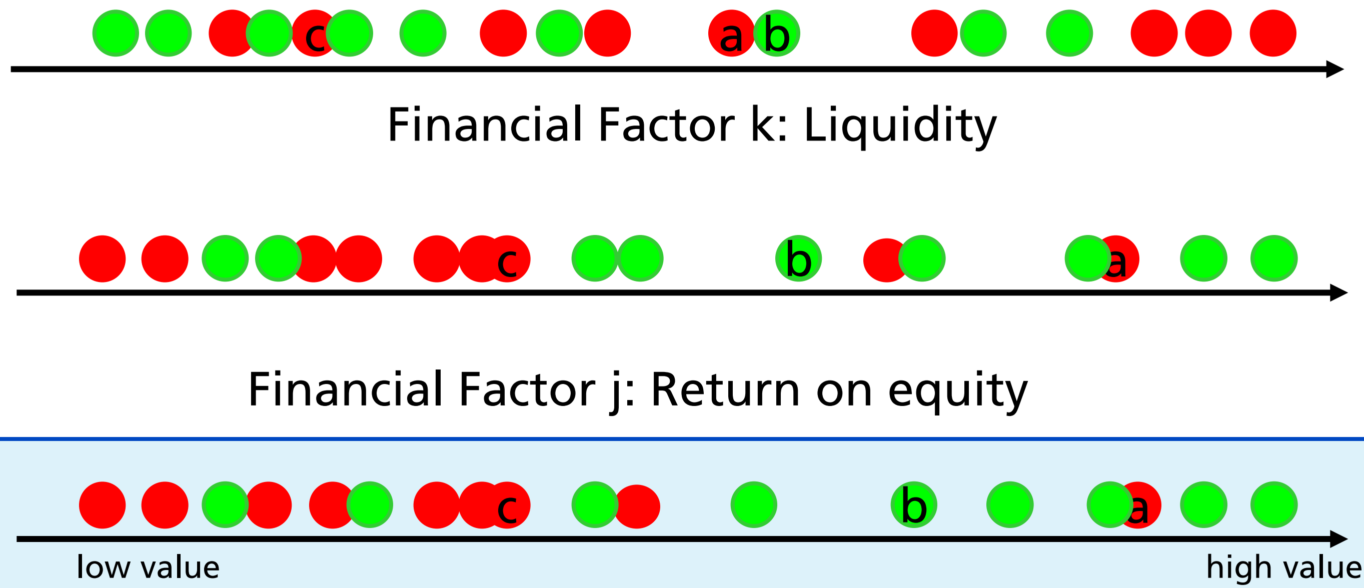
How to incorporate more than one risk driver

The multivariate case: Value added for rank ordering

predictive power



Financial Factor k: Liquidity — 20%

Financial Factor j: Return on equity — 55%

Joined Model: Score = w_1 *(liquidity) + (1-w_1) *(return on equity) — 75%

Combining single factors to a model yields improved predictive power !

How do we obtain a mapping from both factors to PDs? Multivariate **logistic regression** produces factor weights and the mapping to PDs.

performing   defaulted

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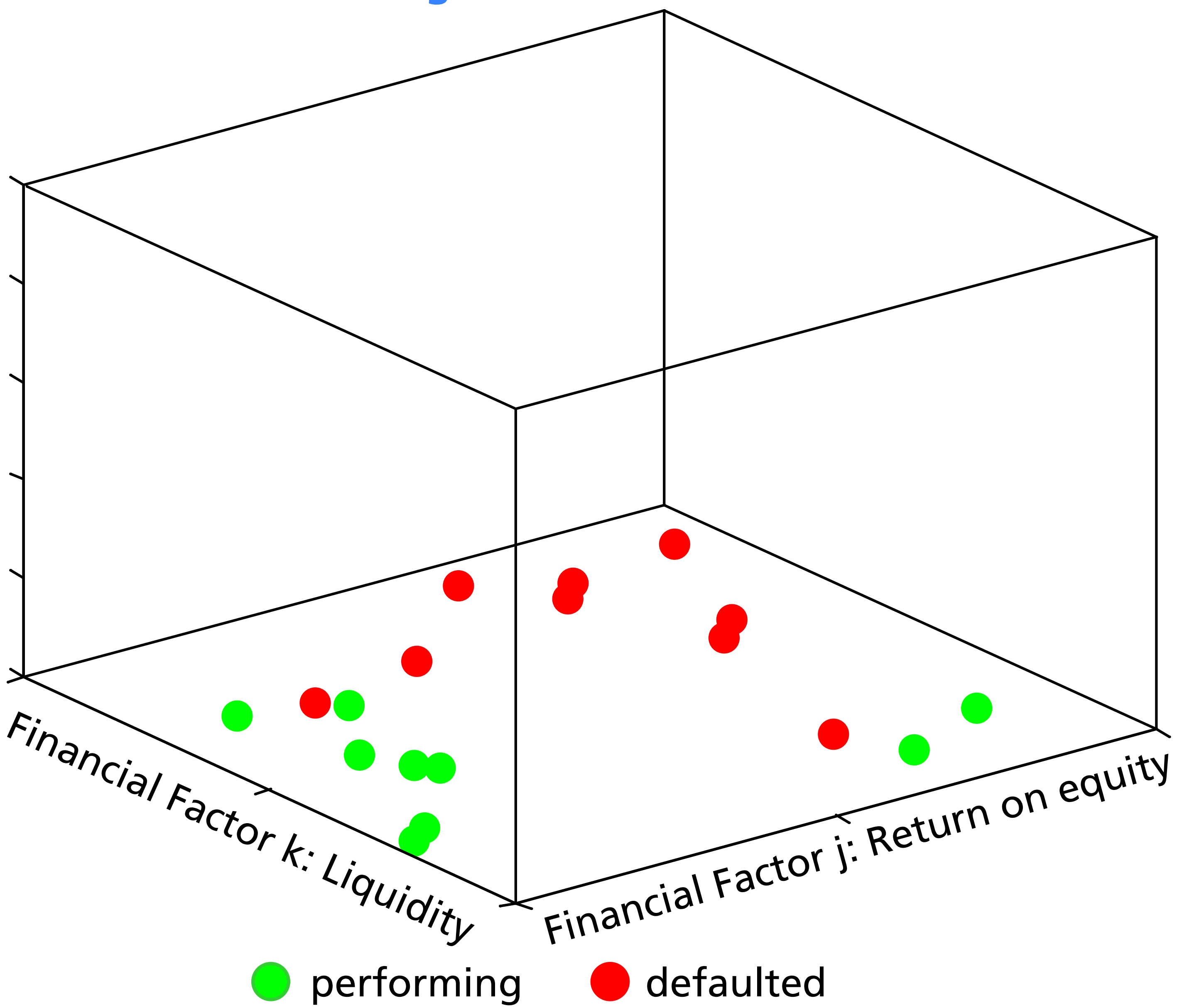
How to incorporate more than one risk driver

Calibration of a two-factor rating tool



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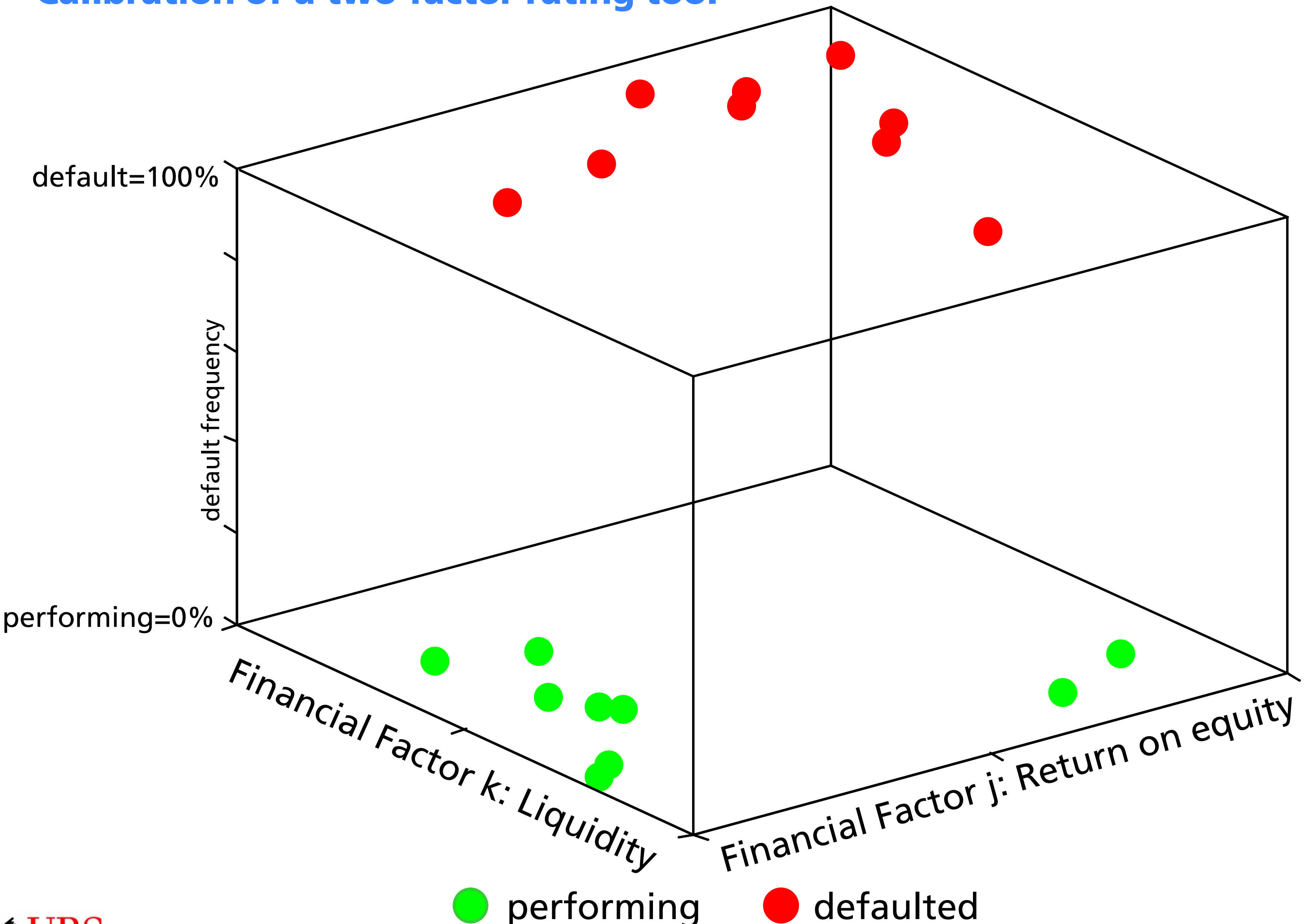
How to incorporate more than one risk driver

Calibration of a two-factor rating tool



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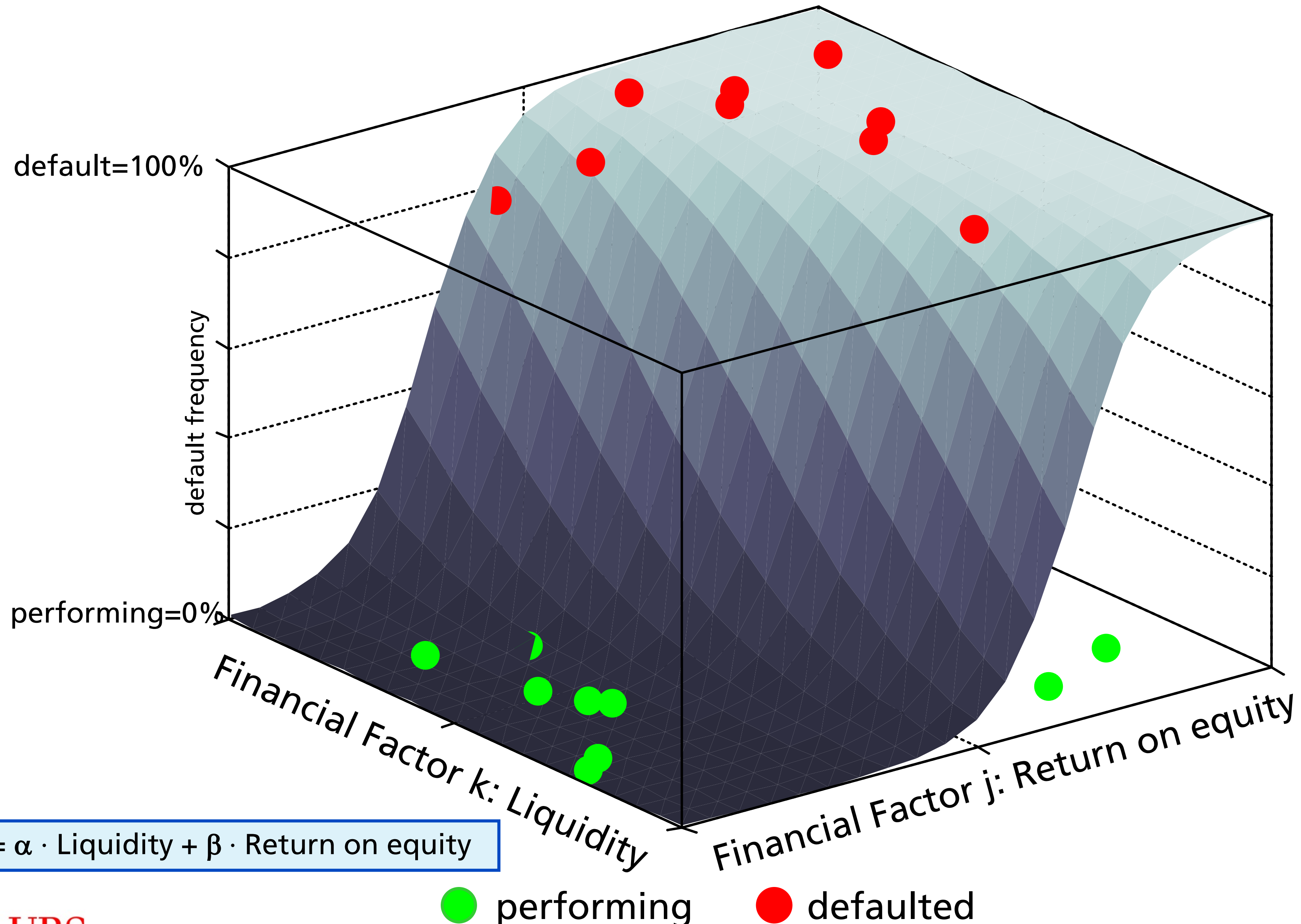
How to incorporate more than one risk driver

Calibration of a two-factor rating tool



Score = $\alpha \cdot$ Liquidity + $\beta \cdot$ Return on equity

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