Credit Risk Programme

Module 3

Decision Tools

Learning Objectives

At the end of this session, you will be able to:

- Understand how application scorecards are constructed and used.
- Understand how behaviour scores are constructed and used.
- Understand how scorecards are translated into Probability of Default predictions.
- Appreciate measures for evaluating scorecard effectiveness.
- Demonstrate understanding of key metrics used to track and evaluate sscorecards.

Underwriting Process

Scenario

Malaysia Credit Cards Application Scorecard with Credit Bureau Data

Background

- A new scorecard was developed to provide better good-bad separation with the incorporation of credit bureau data

Advantages

- Improvement in approval and loss rate management .
- Increased predictability and discriminating power .
- Alignment of booking strategy for applications with and without credit bureau .
- Consistent front-end credit decisioning.

Pre-implementation

- Old scorecard was derived solely from demographic attributes at time of application

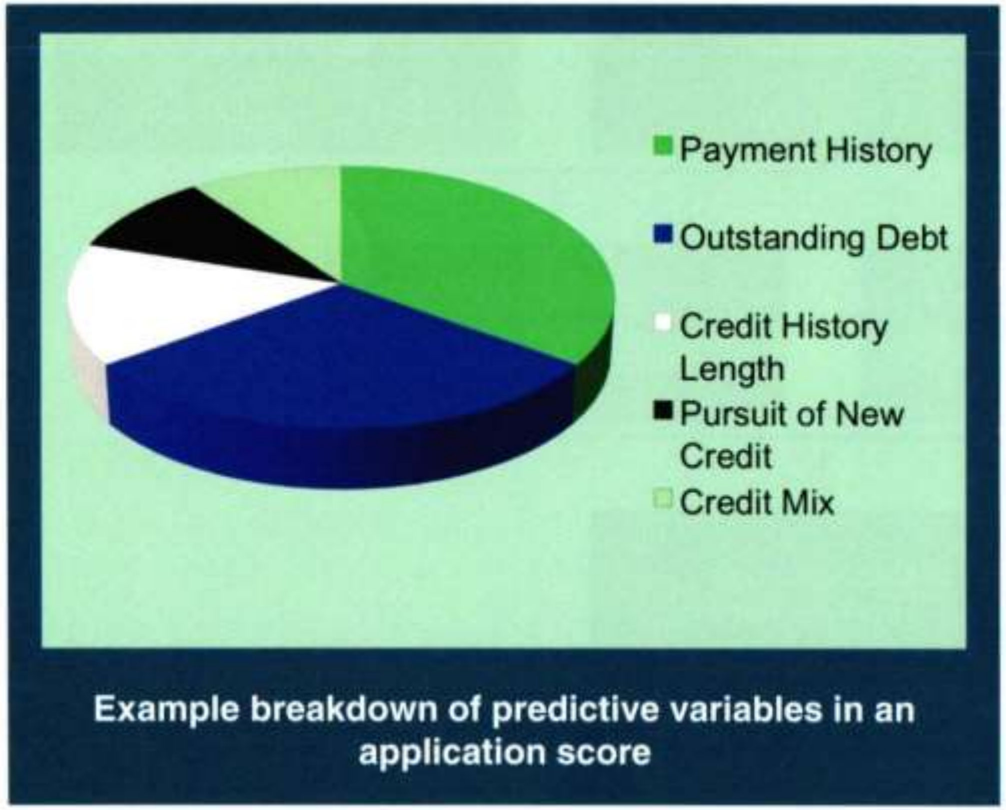
Post-implementation

- Performance improvements on bad rates and risk-adjusted returns

Definitions

Application Score	• Risk ranking tool which is used to evaluate credit applicants at the time of underwriting. It is used to rank order risk of those loans during underwriting and the first six months of the loan.
APR	• Annual Percentage Rate (loan interest rate)
Bad Rate	• #Bad Loans / (#Good Loans + #Bad Loans) Note that the definition of "Bad Loans" is the number of loans which have defaulted or are seriously delinquent within a specific period of time. This is a measure of incidence (i.e. numbers and not severity) and is scorecard specific to include serious delinquency and default
Behaviour Score	• Risk ranking tool which is used to evaluate accounts starting at 6 months on books. Payment and usage behavior become important predictive data for this class of models.
Incidence	• The number, or percent of accounts or borrowers who go into delinquency or default
Odds	• The odds that a customer will be a good account, based on the scorecard performance definition. For example, if you have 2 good accounts and 1 bad account, the Odds are 2:1 and the bad rate is 33%
Severity	• The monetary loss impact of those customers going into delinquency or default
TTD	• Through The Door population; the population of customers who apply for a particular product

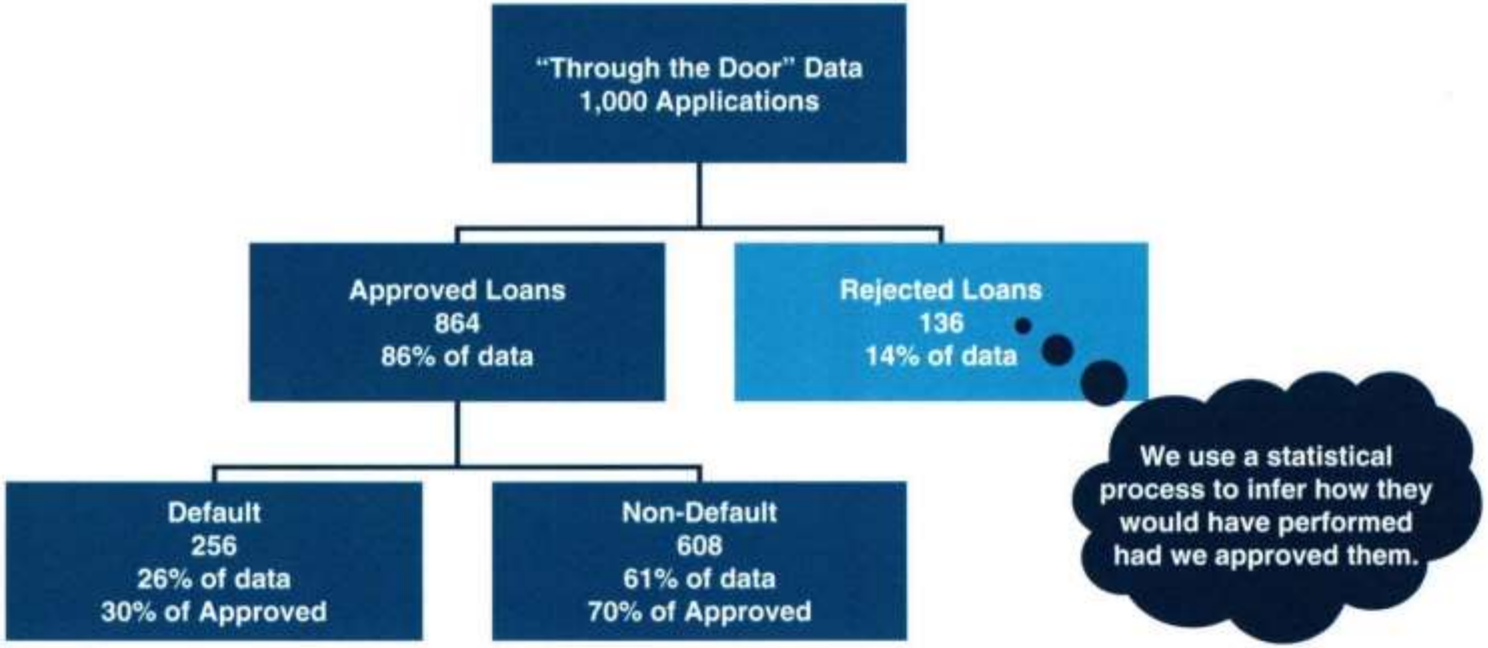
Credit Scoring



- Statistical tool that predicts probability of account becoming delinquent or written-off: the incidence of serious delinquency or default
- Developed from a large / homogeneous population
- Reliable if future applicants perform like past

RB Scorecards are Empirically Derived

- RB scorecards are empirically derived using portfolio data.
- In this data sample, the Default (Bad) Rate was 307o. We can use the data to build a predictive model. However, future behavior of customers will have some changes and shifts



Example Scorecard

PREDICTORS	RANGES	SCORE
Age	18-24	48
	25-27	56
	28-30	58
	31-34	61
	35-42	80
	43-49	75
	Older than 49	65
Outstanding / Limit Ratio for all Credit Cards	0 – 9 %	69
	10% - 39%	81
	40% - 60%	44
	Greater 60%	38
Checking Account	No Checking Account	97
	Less than 0 DM	42
	0 to <200 DM	51
	3: >=200 DM	66
Other Debtor Guarantor	None/Coapplicant	63
	Guarantor	104

PREDICTORS	RANGES	SCORE
Time in Employment	Unemployed	52
	Less than 1 year	64
	1 to < 4 years	77
	More Than 4 years	67
Installment Rate	Low	83
	Intermediate and High	70
	Very High	55
Saving Account Balance	Unknown/No Savings Account	80
	Less Than 500	57
	Greater Than 500 DM	92
Loan Purpose	Car (New)/Others	49
	Repairs/Business	58
	Furniture/Equipment/ Education/ Domestic Appliances	64
	Car (Used)/ Domestic Appliances/ Re-training	85
	Vacation	64

Data and Information Gathering Checklist

Account Level Data at time of application:

- All application data fields (demographics, asset, liabilities)
- All data for both accepted and relected loans
- Other loan / account information
- Credit bureau at time of application
- Product data (amount financed, down payment, term, etc.)
- Marketing data (source, program, inducement)

Portfolio level data:

- Policies in effect at time of application
- Target marketing (past and lor future plans)
- Reject rates
- Application forms (past and future)
- Collection practices (including DRP and bankruptcy)

Data and Information Gathering Checklist

Application System and Forms:

- Code changes
- System purges / archive
- Rejects
- Missing Data - not asked, not answered - exact codes

Check Data Dumps and Frequencies:

- Check completeness - all variables and account volumes present?
- No errors
- No missing data, or documented what is missing and why
- Frequency tables by characteristic (volumes and percent in each category)
- Frequency tables to show volume of data errors or missing data

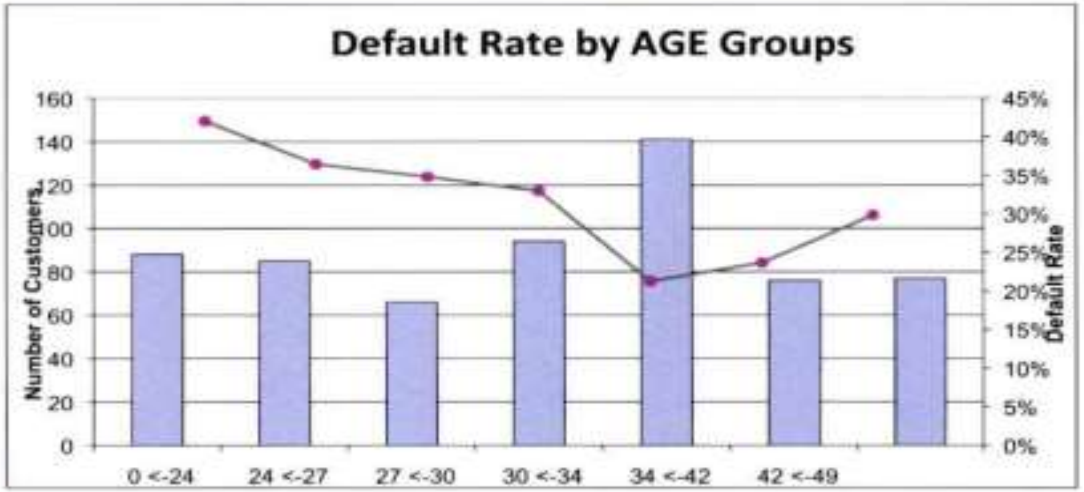
For an application scorecard, we need 2 or 3 years of historical data.
To backtest "through the cycle", we should have 7 years of historical data.
Note: This means that we should not purge historical applications or master file data

The First Step is Exploratory Data Analysis

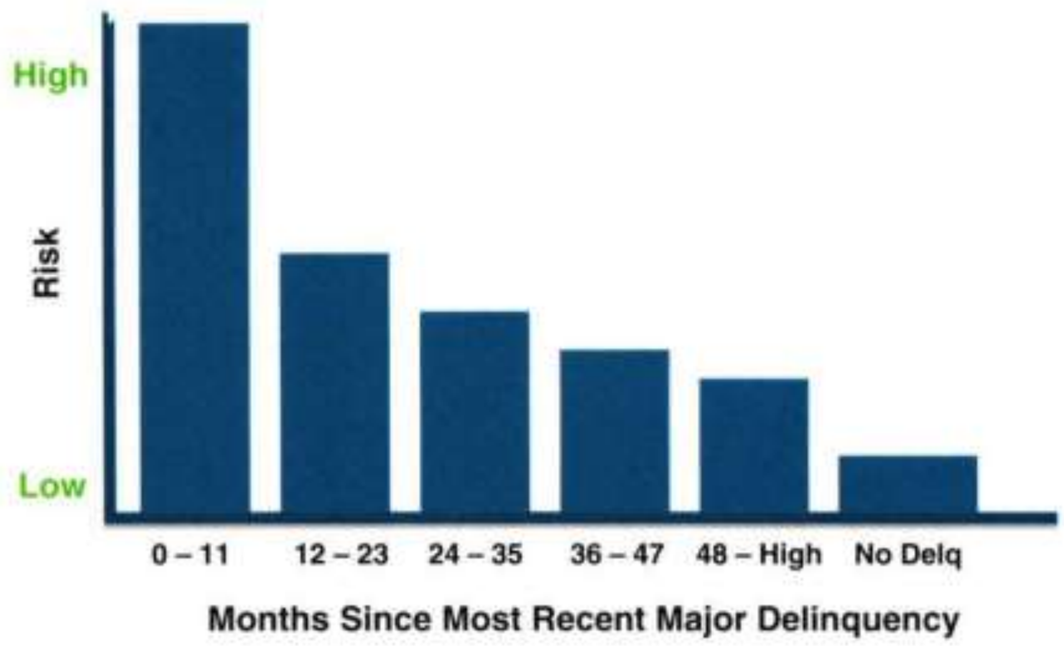
	checkinc	history	purpose	amount	savings	employe	installp	marital	coapp	resident	property	age	housing	existcr	job	telephon	Status
obligor1	1	4	3	1169	5	5	4	3	1	4	1	67	2	2	3	2	good
obligor2	2	2	3	5951	1	3	2	2	1	2	1	22	2	1	3	1	bad
obligor3	4	4	6	2096	1	4	2	3	1	3	1	49	2	1	2	1	good
obligor4	1	2	2	7882	1	4	2	3	3	4	2	45	3	1	3	1	good
obligor5	1	3	0	4870	1	3	3	3	1	4	4	53	3	2	3	1	bad
obligor6	4	2	6	9055	5	3	2	3	1	4	4	35	3	1	2	2	good
obligor7	4	2	2	2835	3	5	3	3	1	4	2	53	2	1	3	1	reject
obligor8	2	2	1	6948	1	3	2	3	1	2	3	35	1	1	4	2	good
obligor9	4	2	3	3059	4	4	2	1	1	4	1	61	2	1	2	1	good
obligor10	2	4	0	5234	1	1	4	4	1	2	3	28	2	2	4	1	reject
obligor11	2	2	0	1295	1	2	3	2	1	1	3	25	1	1	3	1	bad
obligor12	1	2	9	4308	1	2	3	2	1	4	2	24	1	1	3	1	bad
obligor13	2	2	3	1567	1	3	1	2	1	1	3	22	2	1	3	2	good
obligor14	1	4	0	1199	1	5	4	3	1	4	3	60	2	2	2	1	bad
obligor15	1	2	0	1403	1	3	2	2	1	4	3	28	1	1	3	1	good
obligor16	1	2	3	1282	2	3	4	2	1	2	3	32	2	1	2	1	bad
obligor17	4	4	3	2424	5	5	4	3	1	4	2	53	2	2	3	1	good
obligor18	1	0	9	8072	5	2	2	3	1	3	3	25	2	3	3	1	good
obligor19	2	2	1	12579	1	5	4	2	1	2	4	44	3	1	4	2	bad
obligor20	4	2	3	3430	3	5	3	3	1	2	3	31	2	1	3	2	good
obligor21	4	4	0	2134	1	3	4	3	1	4	3	48	2	3	3	2	good
obligor22	1	2	3	2647	3	3	2	3	1	3	1	44	1	1	3	1	good

Starting from the obligor level data in that portfolio

Next we analyze the observed default rates across a set of candidate predictive variables



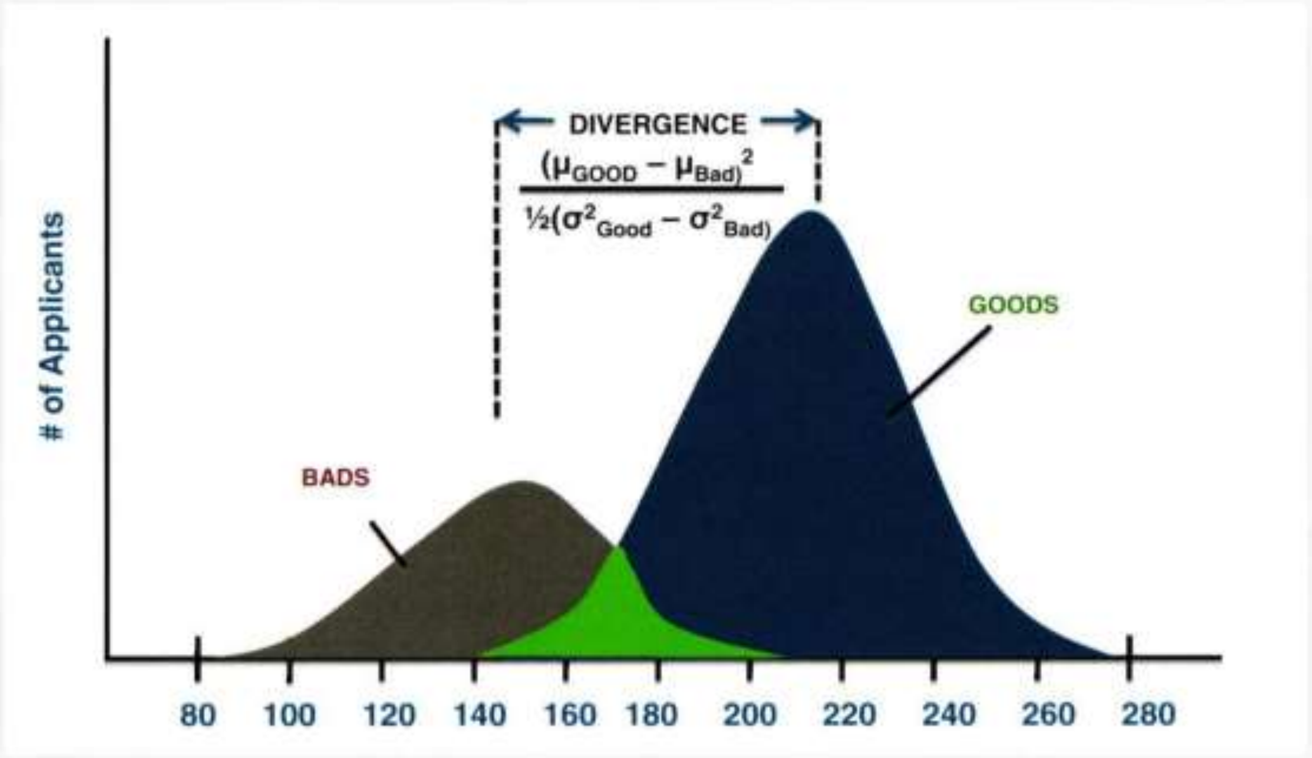
Credit Bureau (or "Off Us") Data is Predictive



For example, we can analyze the customers' historical payment delinquency behaviour on all their credit obligations as seen in the credit bureau. We can analyze:

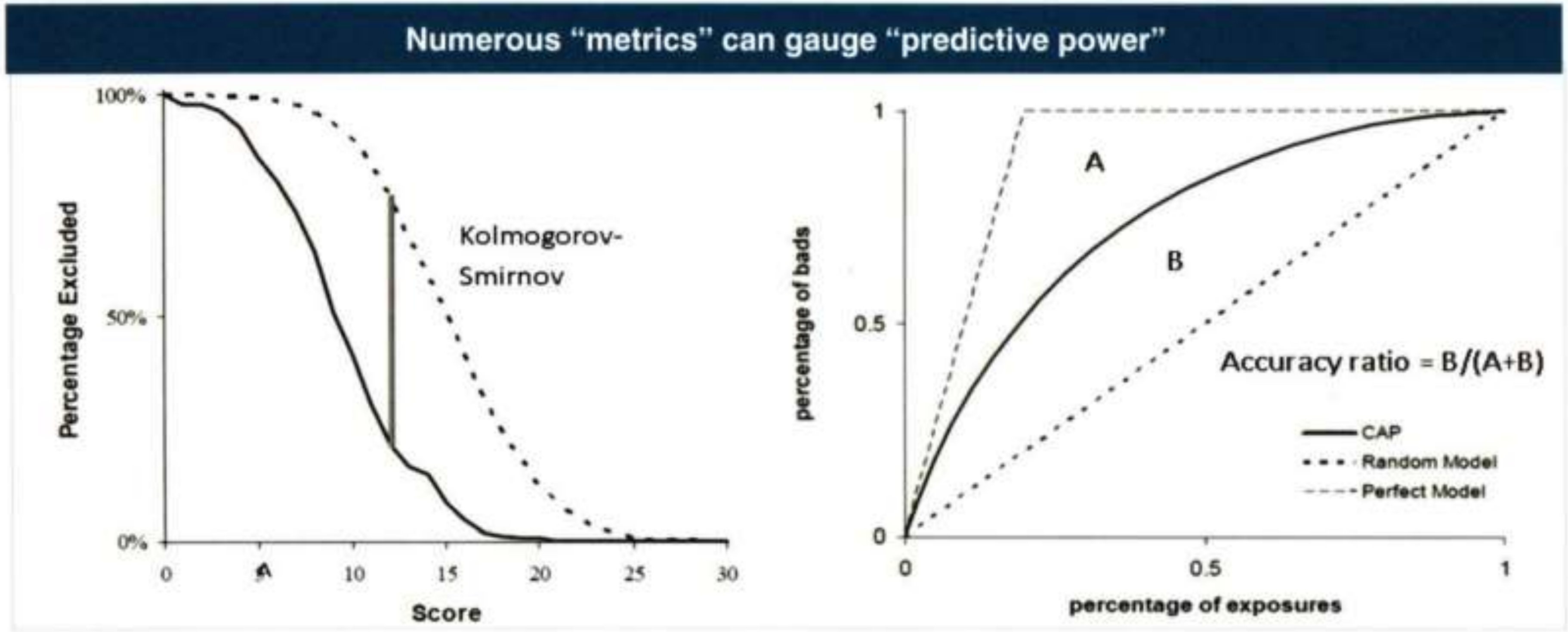
- How recent is the most recent delinquency, collection or public record item?
- How severe was the worst delinquency - 30 days, 90 days?
- How many credit obligations have been delinquent?

Credit Score Distribution



The more separation between peaks, the better the score.
We can measure this using divergence:

How do I know if the Scorecard is Working?



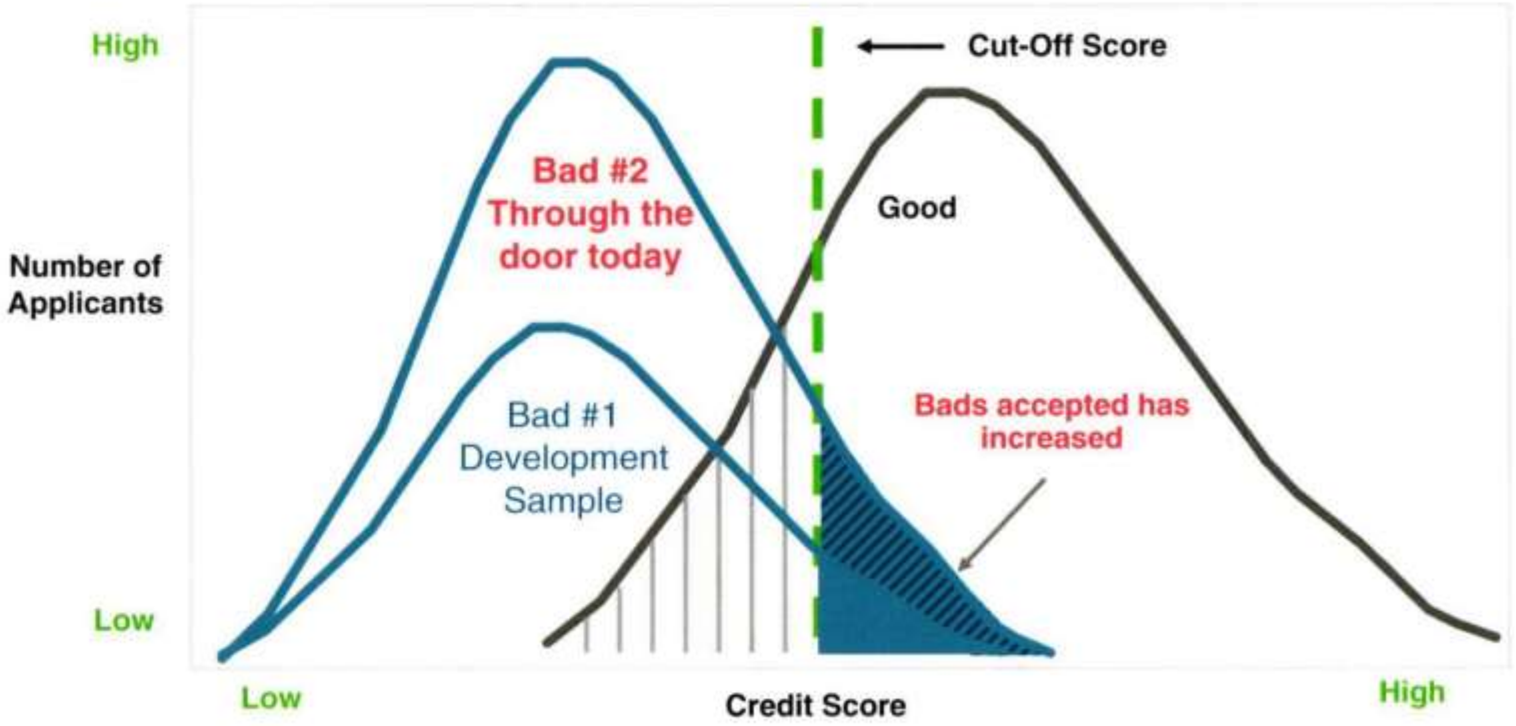
We Must Do Reject Inference

What about accounts rejected in the past?
How do we account for them in our model if we don't know their payment performance?

Credit Scoring

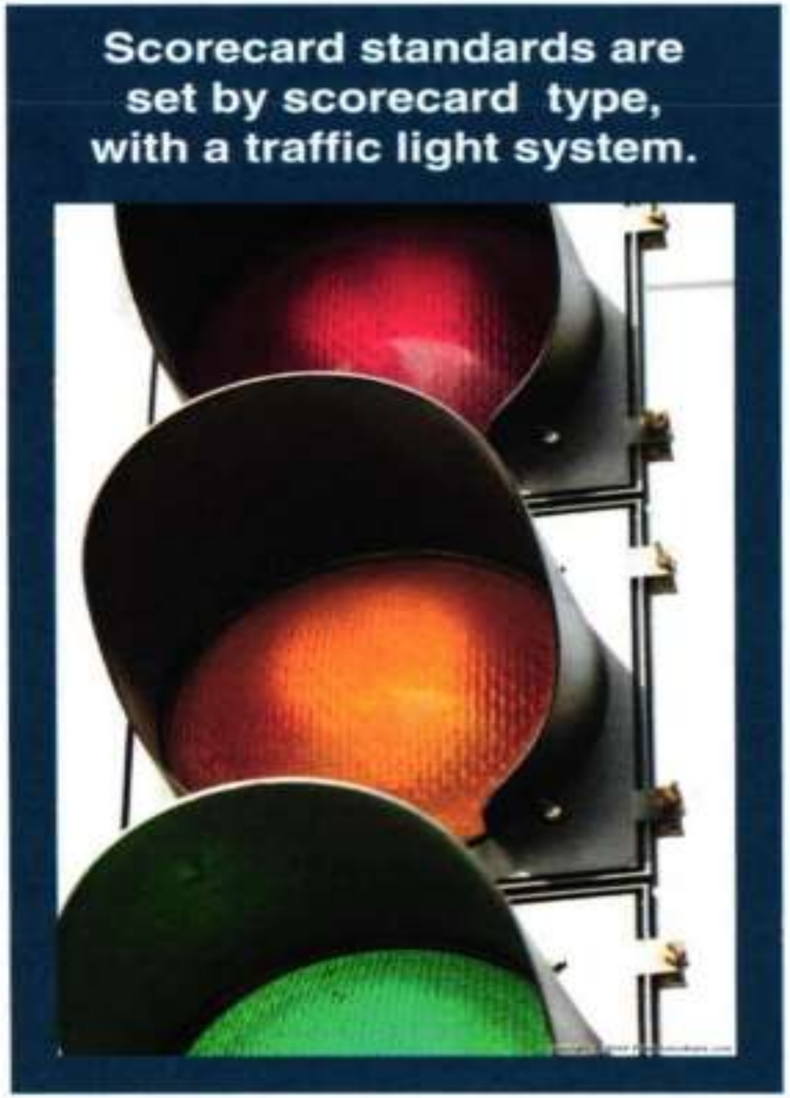
- Book 20,000 goods + 1,250 bads = 21,250 Total
- Booking Rate = 21,250 / 35,000 = 61%
- Bad Rate = 1,250 / 21,250 = 6%

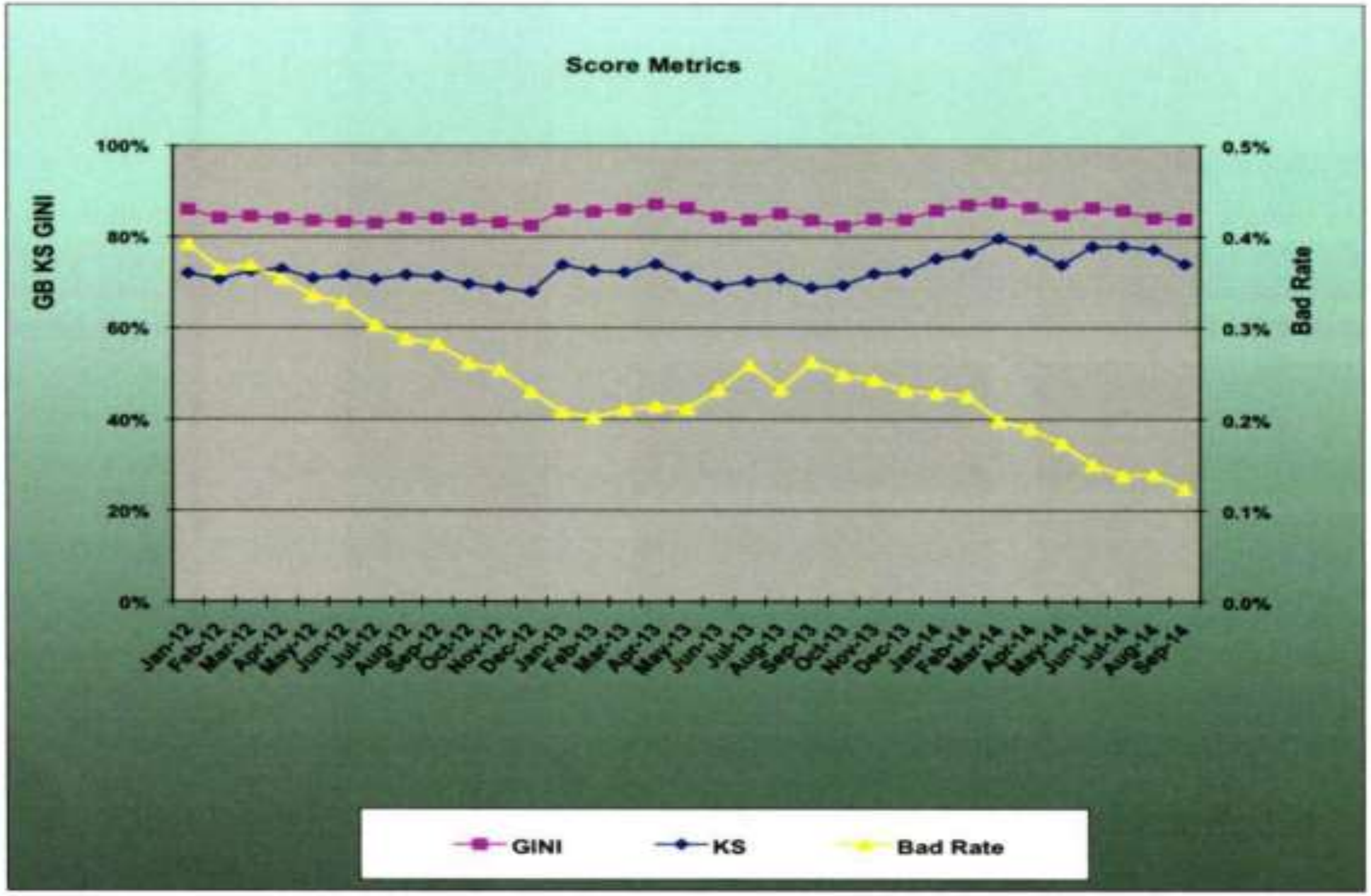
Credit Scoring - Challenges



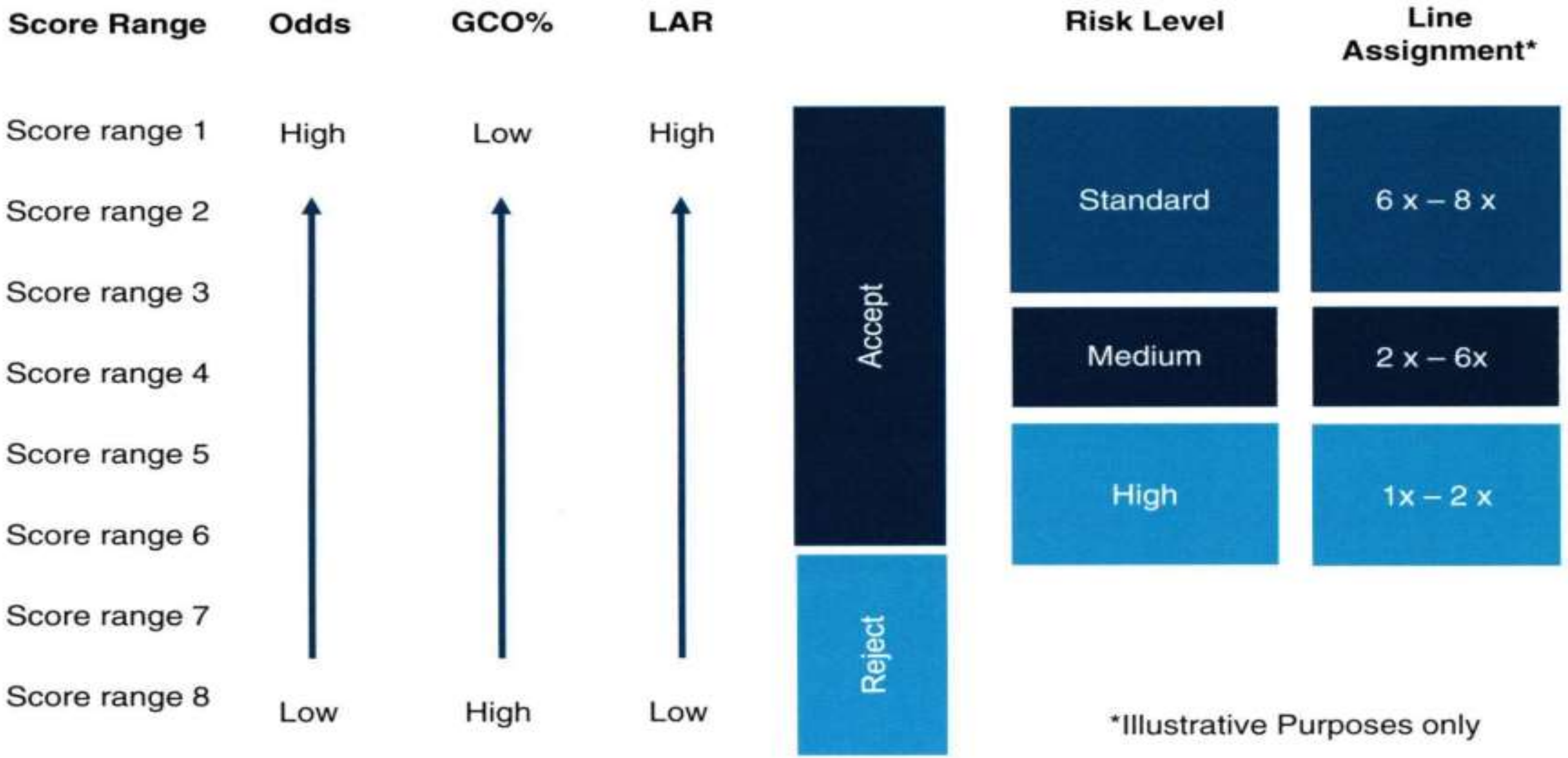
- Live environment presents different "through the door" population from that used to develop the score
- Good scorecards cannot overcome bad targeting

Score Tracking Data





Score Cut Offs



Underwriting Process

Lessons Learned

The impact of positive bureau data on the predictive power a scorecard is material. The financial impact of an improved model can be measured through the improvement of bad rates and approval rates.

Ever Delinquent Scorecard

	Score Approval Rates (%)	Bad Rates (%)	GCO (%)	RAR (%)
Above Cut - Off	67.1	3.23	2.13	16.66
Total Segment		18.92	7.42	11.00
Difference		Reduction of 15.69% (improvement)	Reduction of 5.3% (improvement)	Increase of 5.7% (improvement)

Never Delinquent Scorecard

	Score Approval Rates (%)	Bad Rates (%)	GCO (%)	RAR (%)
Above Cut - Off	85.4	1.50	2.88	17.76
Total Segment		6.84	6.14	14.14
Difference		Reduction of 5.3% (improvement)	Reduction of 3.3% (improvement)	Increase of 3.6% (improvement)

Credit Bureau Variables in a Scoring Model

Characteristics	Attributes	Points
Number of months since the most recent derogatory public record (**Payment History**)	No pubic record 0 – 5 6 – 11 12 – 23 24+	75 10 15 25 55
Average balance on revolving trades (**Outstanding Debt**)	No revolving trades 0 1 – 99 100 – 499 500 – 749 750 – 999 1000 or more	30 55 65 50 40 25 15
Number of months in file (**Credit History Length**)	Below 12 12 – 23 24 – 47 48 or more	12 35 60 75
Number of inquiries in last 6 mos. (**Pursuit of New Credit**)	0 1 2 3 4+	70 60 45 25 20
Number of Bankcard Trade Lines (**Credit Mix**)	0 1 2 3 4+	15 25 50 60 50

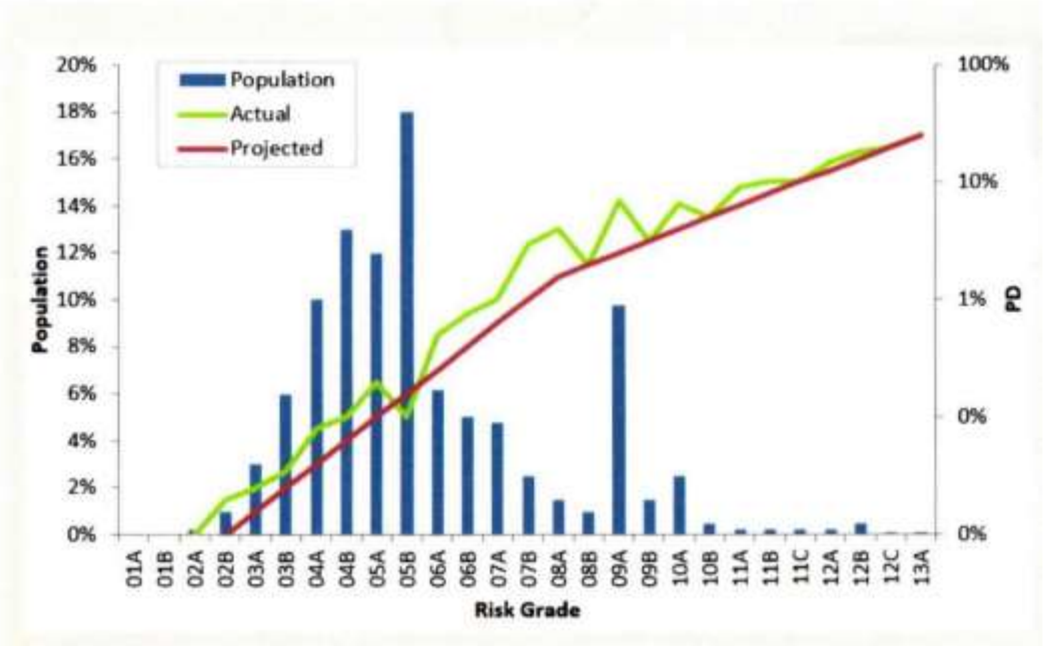
Translating Scores into PD

We can estimate a simple formula:

- A formula which translates SCORE into PD
- It turns out there are many functions
- It is usual to use a funny looking one…the Logit
- WHY?
- Convenience mainly – this number gets larger the larger score is, and is always between 0 and 1
- Few other reasons

$$PD = \frac{1}{1 + \exp(\alpha + \ \beta Score)}$$

Example PD Monitoring



- The table details the actual vs. predicted monitoring of PD on a monthly basis at the total portfolio level.
- The monitoring shows that the PD model has been under-predicting.
- The PD model was redeveloped.

Score PD Risk Grade Profitability!

Score	Bad Rate	PD	Risk Grade	Financial Metric #1
620 – 629	2.5%	1.0%	7A	
610 – 619	3.0%	1.2%	7B	
600 – 609	3.5%	1.5%	8A	
570 – 599	4.5%	2.0%	8B	
560 – 569	6.0%	3.5%	9A	
550 – 559	8.0%	5.0%	9B	

1. Score is built to predict bad rate

2. Measure observed PD score by hand

3. Risk grade is just a new label foreach row

4. Measure the financial metric of your choice (RORWA, RLM)

Overrides

Borderline Scores and Low Overrides

Analyze the negative item(s) that contributed to the applicant missing the cut-off:

1. Single vs. Pattern
2. When it occurred: recent or long ago
3. Stated reason for the delinquency / write off

Compensating Factors:

- Stability of employment –a long-time customer
- Other financial resources - good recent behavior

- **If approved – “Low–Side – Override”**
- **High Side Override**
- An applicant is rejected even though he or she passed the credit score cut-off. Possible reasons:
    1. Verification was unsuccessful
    2. Exceeds maximum debt burden guidelines
    3. Exceeds maximum LTV guidelines
    4. Others (high-risk profile etc.)

Credit Limit Assignment

Scenario

Odds are the ratio of good customers to each bad customer. Break-even odds are the number of good customers which are needed in a particular group of customers to pay for one bad customer's loss.

Here's an example from a credit card portfolio, for a particular cell of customers, let's say our observed recent historical data is:

Loss = $1,000 per customer on average

Revenue = $100 per customer on average

Cell Breakeven Odds = 1 ,000 / 100 = 10:1

- Revenue from ten customers is needed to cover the loss from one customer.
- $100 revenue x 10 customers = $1 ,000 revenue:

What if we are given a hurdle rate of 8:1 break-even odds. Can we lend in this cell?

What if we are given a hurdle rate of 15:1 break-even odds. Can we lend in this cell?

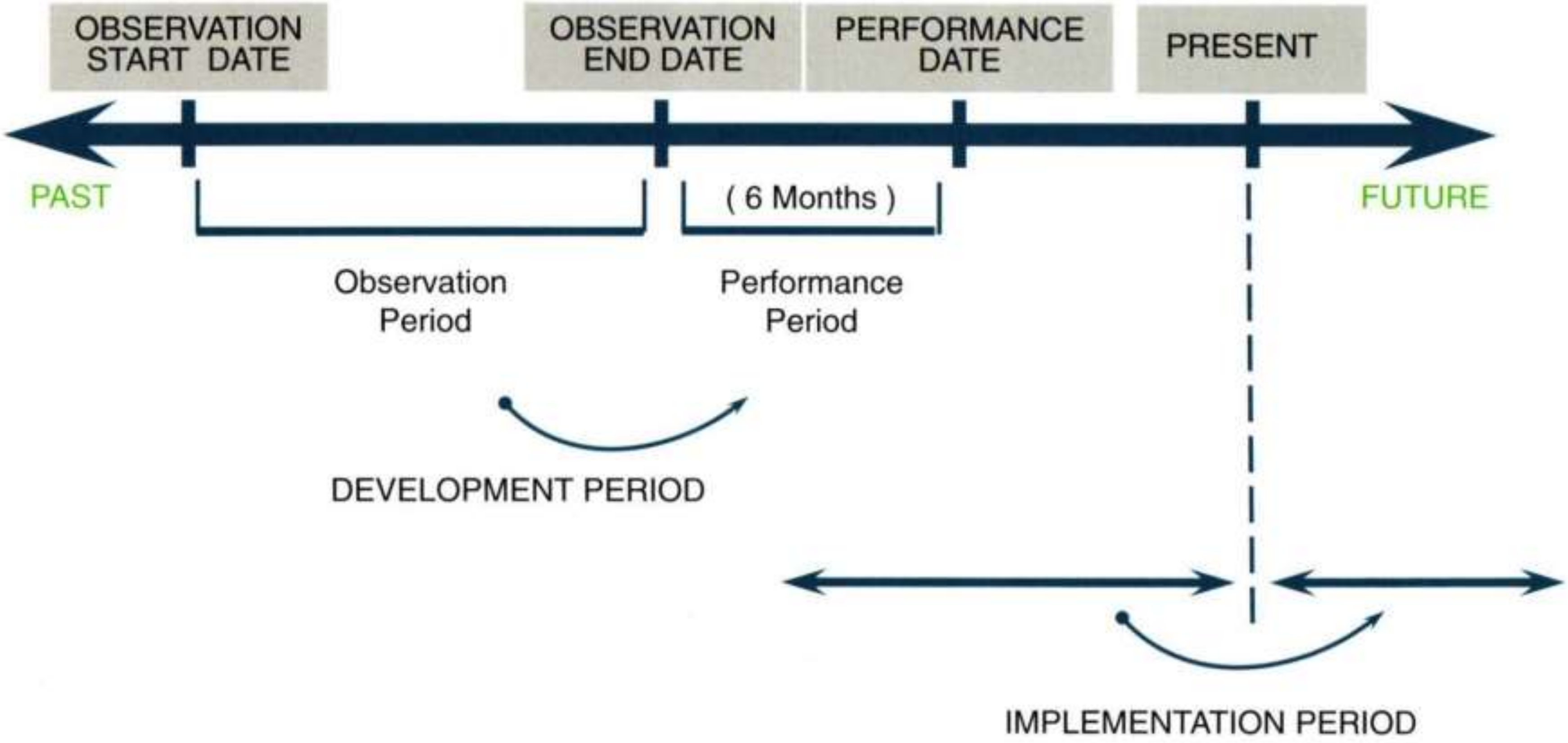
What would be if implication if our Cost of Funds for the portfolio increased by 20'/o?

What if the recovery rate for this portfolio increased by 10% for this portfolio due to improved collection discipline and the use of enhanced tools?

Industry Usage of Models Across the Life Cycle

	Targeting Customers	Booking Accounts	Managing Customers
Risk Score	X	X	X
Revenue Score	X	X	X
Collection Score			X
Recovery Score			X
Attrition Score			X
Fraud Score	X	X	X
Response Score	X		X
Bankruptcy Score	X	X	X
Household Cluster	X		X
Forecast	X	X	X

Behavior Scorecards Differ from Application Scorecards



Behaviour Scores Use More Predicitve Customer Account Activity

Characteristics	Attributes	Points
Months on Books (Non-Monetary)	1 - 6 7 - 12 13+	75 90 110
Number of delinquencies in last 6 mos. (Delinquency)	0 1 - 3 4+	105 95 85
Current balance as a % of maximum balance lifetime (Financials - usage)	0 – 10 11 – 25 26 – 40 41 – 90 91+	60 75 60 35 12
Payment to balance ratio (%) (Financials - payments / purchases)	0 – 20 21 – 50 51+	85 95 100
Number of cash advances ever (Lifetime)	0 1 – 2 3 – 5 6+	80 65 60 45

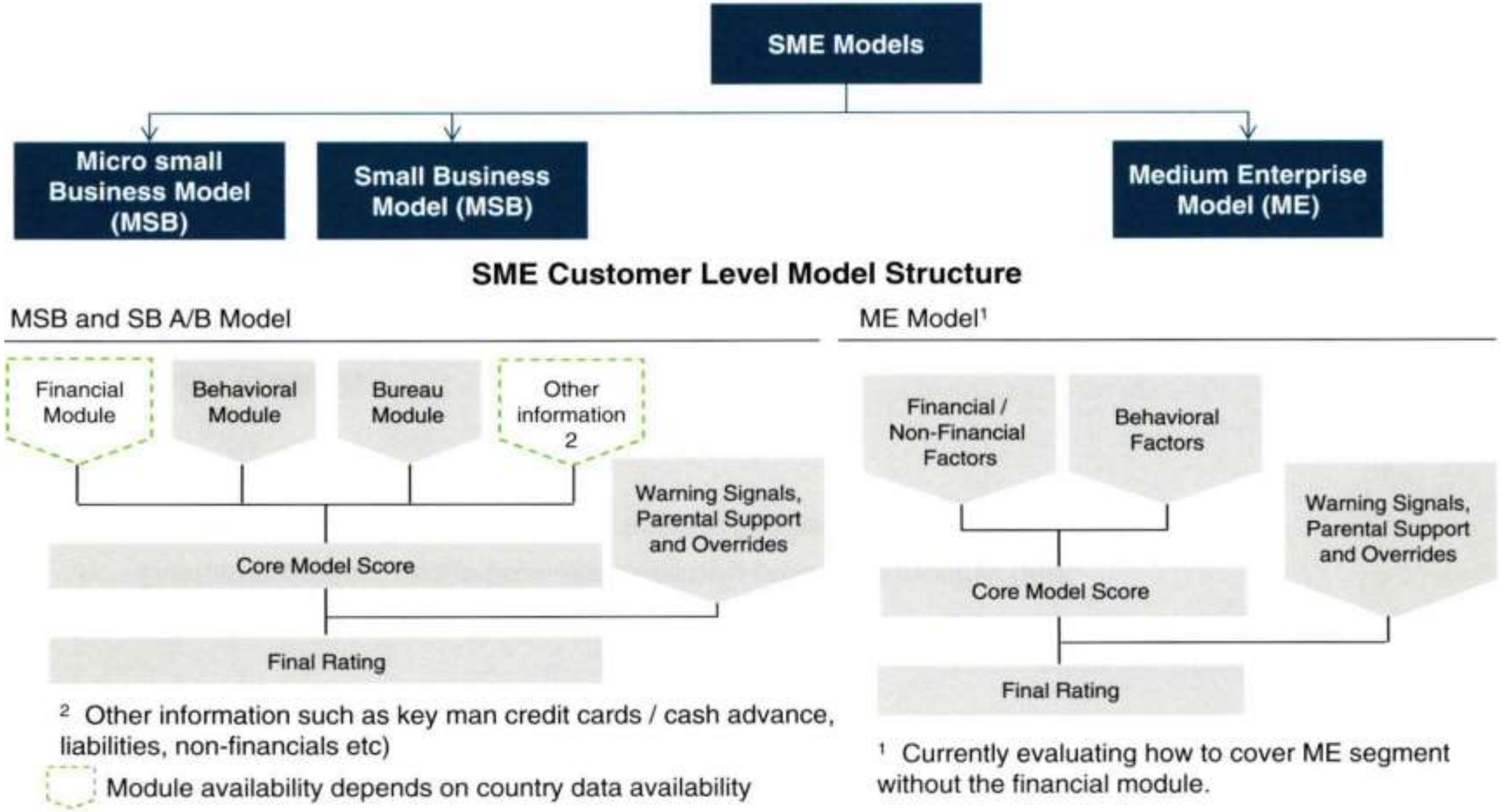
Behaviour Scorecards for Different Products

- **Credit Card and Revolving Products**
  - Customer product usage provides extremely predictive monthly data
  - Actions can be taken based on the scorecard (credit limits, renewal, etc)

- **Instalment Products**
  - There is less information than revolving, but is still more predictive than an application scorecard after 6 months on books.
  - The limitation is on the bank's ability to act upon the score.

The SME Customer Level PD Models

- **Business Banking uses the Global SME customer level PD models which are composed of several modules.**



CORESTRAT

SME Model Coverage

PD Models		BIL/GIL	BWC	Mortgage/LAP
North East Asia and Greater China	HK	MSB/SB/ME	MSB/SB/ME	NIL
	CN	New SB[1]/ME	New SB[1]/ME	NIL
	TW	SB (2016)	NA	NA
	KR	New models (2016)		
South East Asia	SG	MSB/SB/ME	MSB/SB/ME	NIL
	MY	MSB/SB/ME	MSB/SB/ME	App Scorecard
	TH	SB (pending)	NA	NIL
	ID	NIL	NA	NIL
South Asia	IN	MSB/SB/ME	MSB/SB/ME	NIL
	BD	NIL	EMM	NIL
Africa		NA	EMM	NIL

[1] New SB developed in China is a combined MSB and SB scorecard

Indicates scorecard absent with existing exposure

A Few Observations for SME Models

Size and composition of the SME drives input data

- Smaller businesses with single proprietor may use application and credit bureau report of the owner
- As the business grows, data sources change. We add audited financials, and then a small business bureau report as they become available
- Each country will define the data to be used for particular segments based on the market and available data sources

Limitations

Technical Limitations

- Since we build models on portfolio historical data, our assumption is that the future will mimic the past
- Performance is dependent upon
  - Environment
  - Prospect/account profile
- Predictiveness limited by the data available for model development
- Scores are not individual odds quotes. Scorecards are a static rank ordering tool.
- Outliers should be treated with care.
- Data integrity affects the results

Practical Limitations

- Establishing and adhering to policies
- Overrides should be applied in a limited, appropriate fashion
- Automating implementation of scoring and strategies
- Training staff who use scoring as part of their decision-making process
- Developing effective strategies
- Evaluate ongoing scorecard/strategy performance

Points to Remember

Success factors for credit scoring include:

- Establish and adhere to policies.
- Override in a limited, appropriate fashion.
- Automate implementation of scoring and strategies.
- Train staff who use scoring as part of their decision-making process.
- Develop effective strategies.
- Evaluate ongoing scorecard/strategy performance using statistical measures and test & learn (champion/challenger) strategies
- Track and monitor through the door distribution to identify any significant shift in the customer sourcing mix

Questions