

4th Seminar on Data Science and Analytics

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Application of predictive models in the banking industry

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Live Poll



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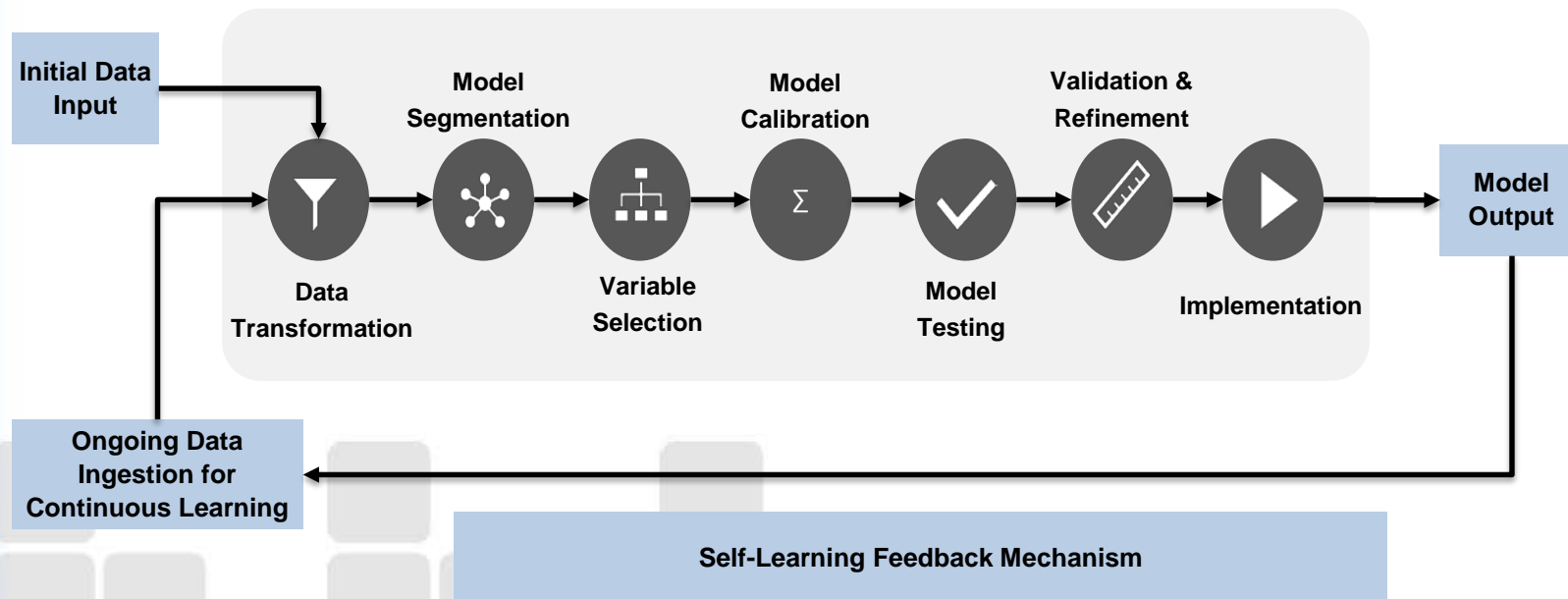


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A brief on predictive models

“Predictive modeling is a statistical technique that works by analyzing historical and current data and generating a model to help predict future outcomes.” – Gartner

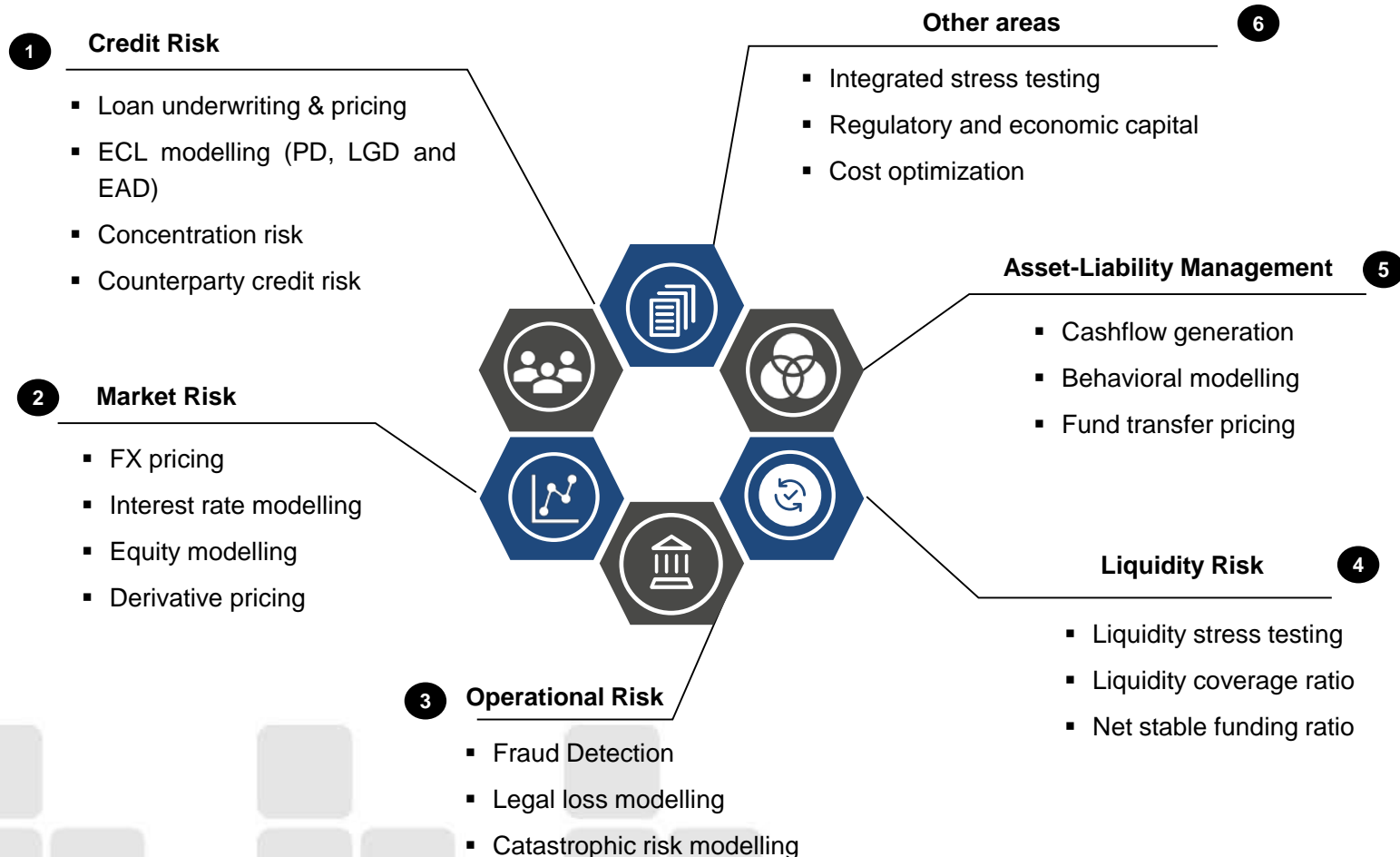
The process of predictive modelling



Key drivers for increased usage of predictive models



Application of predictive models in banking



Commonly used predictive modelling techniques in banking*

Technique	Credit Risk	Market Risk	Operational Risk	Liquidity Risk	Asset-Liability Management
Linear Regression		<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Logistic Regression	<input checked="" type="checkbox"/>				
Time Series		<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Decision Trees	<input checked="" type="checkbox"/>				
Random Forests	<input checked="" type="checkbox"/>				
Neural Networks	<input checked="" type="checkbox"/>				
PCA		<input checked="" type="checkbox"/>			<input checked="" type="checkbox"/>
K-Means clustering	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	
Gradient boosting	<input checked="" type="checkbox"/>				

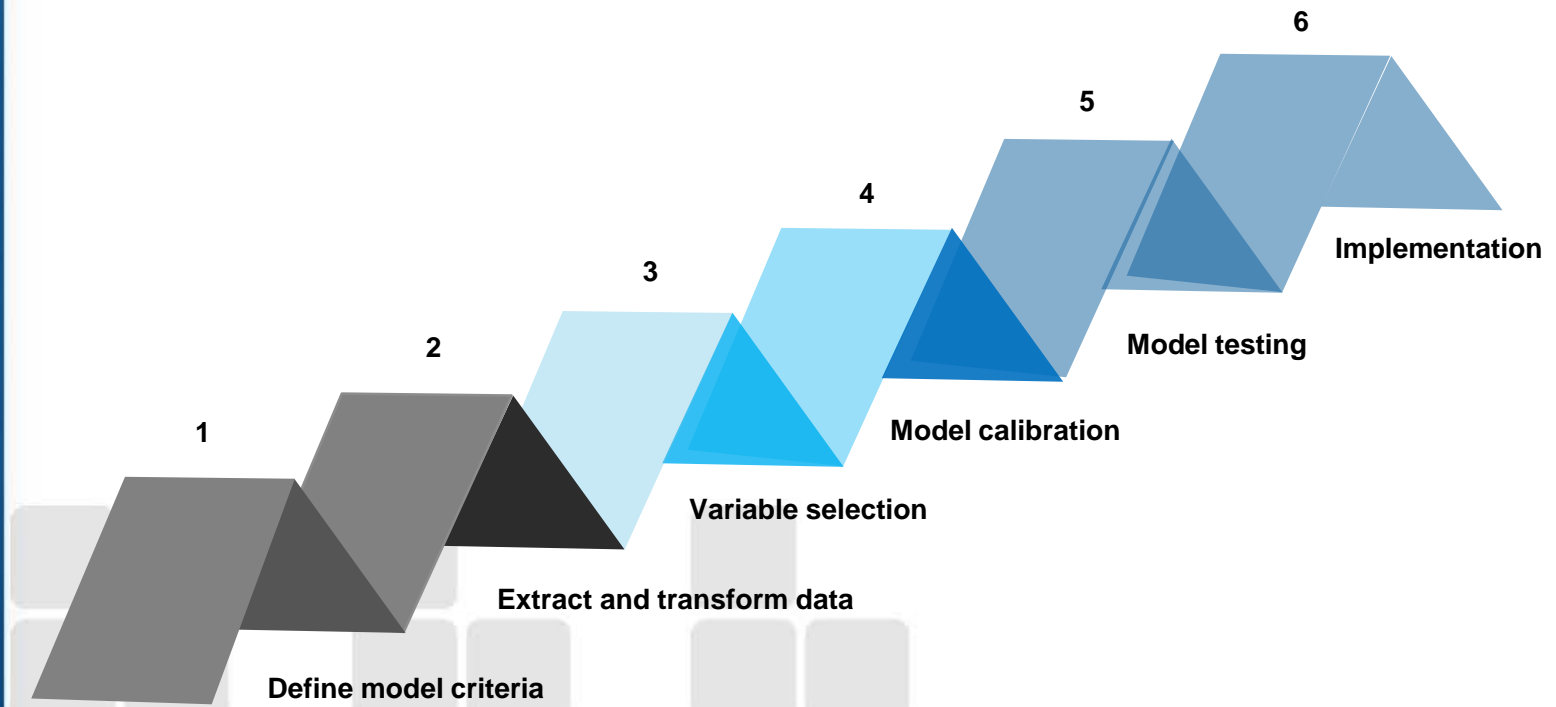
*Techniques and mapping shown above might not be comprehensive

Case study 1: Credit scoring models

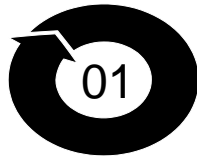


A medium sized bank – XYZ, has recently developed and implemented a credit scoring model for its corporate credit portfolio. The credit scoring model is used to monitor credit health of existing corporate obligors and assess new corporate loan applications.

Process followed by bank to develop and implement the credit scoring model



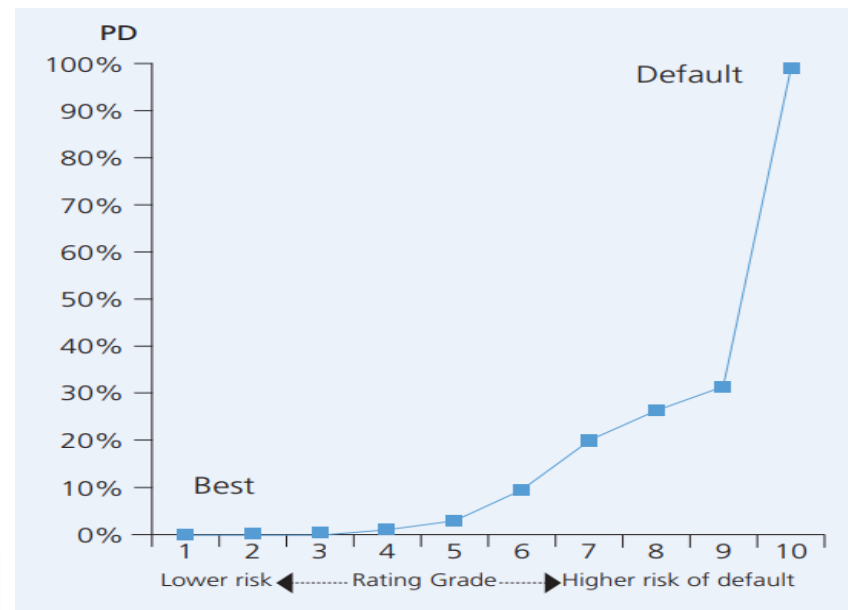
Case study 1: Credit scoring models



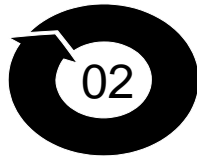
Define model
criteria

- Model segmentation choice (Retail / Corporate / SME) – **Corporate**
- Required model outcome - **Number of rating outcomes to differentiate the risk of their borrowers. A range of 20 grades**
- Forecast horizon: **1-year PD**
- Default definition: **90 days past due (DPD)**

Simple
illustration of
model outcome

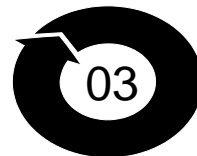


Case study 1: Credit scoring models



Extract and transform data

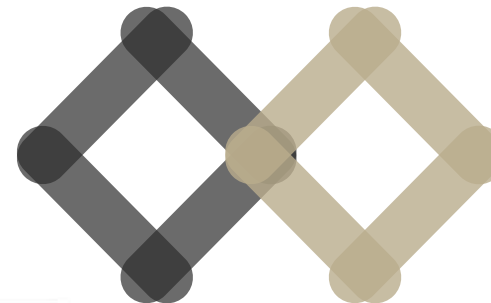
- Sample definition – Each rating grade requires a **sample of 1000 companies** and for **every 10 non-defaults, we need 1 default** in the sample
- Historical data period – Minimum period of **5 years**
- Type of data - financial measures such as **profitability, leverage, liquidity, cash flow adequacy** etc. obtained from **company financial statements**.
- Transformations – **missing values, outlier treatment, standardization** (log-value or ratios)



Variable selection

Quantitative variables

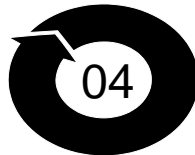
- Profitability
- Interest coverage
- Leverage
- Cash flows
- Liquidity
- Growth rates
- Operating cash flow/debt
- Debt/equity
- Profit margin
- Current ratios



Qualitative variables

- Reputation
- Track record
- Credibility
- Shareholding structure
- Industry profile
- Market position
- Management profile
- Shareholder support
- Parent strength

Case study 1: Credit scoring models



Model calibration

- Training vs testing dataset choice – **75 % of the sample data to be treated as training dataset while 25 % to be treated as testing dataset**
- Model framework – **Logistic regression framework**
- Measure used variable selection – **Information value criterion (IV)**

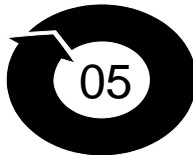
Logistic
regression
model
framework

$$p = \frac{\exp(\beta_0 + \beta_1 \cdot x_1 + \dots + \beta_n \cdot x_n)}{1 + \exp(\beta_0 + \beta_1 \cdot x_1 + \dots + \beta_n \cdot x_n)}$$

where in the above

- p is the probability of default
- x_i is the explanatory factor i
- β_i is the regression coefficient of the explanatory factor i
- n is the number of explanatory variables

Case study 1: Credit scoring models



Model testing

Information Value (IV)

- Measure used to assess discriminatory power of selected variables – **Information value criterion (IV)**
- Measures used to assess model accuracy – **GOF and Accuracy ratio**
- Measures used to assess discriminatory power of model – **ROC and confusion matrix**

$$IV(x) = \sum_{i=1}^{N(x)} \left(\frac{g_i}{g} - \frac{b_i}{b} \right) \cdot \log \left(\frac{\frac{g_i}{g}}{\frac{b_i}{b}} \right)$$

where,

- $N(x)$ is the number of levels in the variable x
- g_i represents the number of goods (no default) in category i of variable x_i
- b_i represents the number of bads (default) in category i of variable x_i
- g represents the number of goods (no default) in the entire dataset
- b represents the number of bads (default) in the entire dataset

Classification power	Information Value
Poor	<0.15
Moderate	Between 0.15 and 0.4
Strong	>0.4

Case study 1: Credit scoring models



Goodness of Fit (GOF)

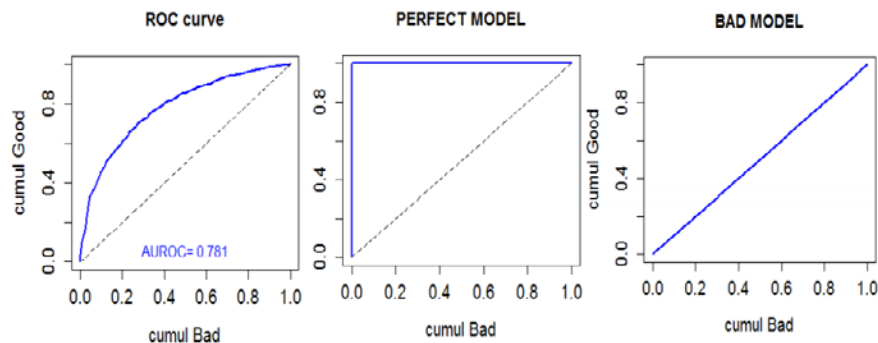
- The model predictions for every company in the test sample are grouped into say 10 percentile groups.
- Subsequently, the average PD is calculated for each group.
- Based on the total obligors in each group, derive the expected number of defaults per group.
- This is then compared to the actual number of realized defaults per group.
- This information is summarized for all 10 groups to derive the statistic that indicates how well the model predicts.

Company	Group	Predicted PD (by Model)	Average PD of Group	Expected no.of defaults (Group)	Realised no. of defaults (Group)	Accuracy Stat (Group)
A		1.00%				
B	1	2.00%	2.67%	0.08	0.01	85%
C		5.00%				
D		7.00%				
E	2	8.00%	9.00%	0.27	0.50	42%
F		12.00%				
:	3	:	:	:	:	:
:	4	:	:	:	:	:

Case study 1: Credit scoring models

ROC Curve

- ROC stands for “Receiver Operating Characteristic”
- The ROC curve is the plot between sensitivity and (1- specificity). (1- specificity) is also known as false positive rate and sensitivity is also known as True Positive rate.
- A perfect model would show a ROC curve that consists of two straight lines: From (0,0) to (0,1) and from (0,1) to (1,1), i.e. very steep.
- A model with no predictive power would have a ROC curve that follows the diagonal, since that would imply that for every cut-off value we find an equal number of goods and bads



Predictive Power	Area Under ROC
Acceptable	>70%
Good	>80%
Very Good	>85%

Case study 1: Credit scoring models

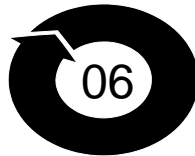
Confusion Matrix

- Used to test model's classification results against the actual observed classification.
- "True Positive Rate" corresponds to the fraction of Goods that are correctly classified [in the example below $7014/(7014+3171)$]
- "True Negative Rate" corresponds to the fraction of Bads that are correctly classified (in the example below $357/(357+178)$).

	Predicted Bad	Predicted Good
Observed Bad	357	178
Observed Good	3171	7014

Predictive Power	TP & TN rate
Acceptable	>60%
Good	>70%
Very Good	>85%

Case study 1: Credit scoring models



Implementation

- Instead of having distinct PDs for each borrower, XYZ devised **percentile groups** that **map to their internal rating scale with a number of 20 rating grades**
- Both **existing and new corporate borrowers** are evaluated with the model and given a rating (with corresponding PD) that is **commensurate with their credit profile**.

Mapping PDs to banks internal rating scale

Rating

1.	AAA
2.	AA+
3.	AA
4.	AA-
5.	A+
6.	A
7.	A-
8.	BBB+
9.	BBB
10.	BBB-
11.	BB+
12.	BB
13.	BB-
14.	B+
15.	B
16.	B-
17.	CCC+
18.	CCC
19.	CCC-
20.	D

Each rating grade maps to a PD band. These PD can be re-calibrated when underlying risk profiles or lending conditions change.

PD Masterscale Risk Ranges

	Low	High
	0.0000%	0.0119%
	0.0119%	0.0168%
	0.0168%	0.0240%
	0.0240%	0.0346%
	0.0346%	0.0500%
	0.0500%	0.0733%
	0.0733%	0.1095%
	0.1095%	0.1636%
	0.1636%	0.3033%
	0.3033%	0.5108%
	0.5108%	0.8573%
	0.8573%	1.5114%
	1.5114%	3.4872%
	3.4872%	5.9459%
	5.9459%	7.7740%
	7.7740%	10.0928%
	10.0928%	12.5000%
	12.5000%	15.0000%
	15.0000%	25.0000%
	25.0000%	99.9999%

Case study 2: Capital modelling and stress testing

As a response to the 2007-08 financial crisis, the federal reserve enforced CCAR – ‘Comprehensive capital analysis and review’, to provide an assessment of the health of systematically important banks in the United States and overall US banking sector.

Coverage

- CCAR risk charge covers retail banking, wholesale banking, trading, counterparty credit risk, operational risk, PPNR, fair value options and loans held for sale, AFS/ HTM securities.

Econometric Models

- Models used to derive forward-looking capital ratios need to be driven by economic intuition i.e. econometric models

Supervisory Stress Scenarios

- Forwarding looking capital ratios need to be computed under three supervisory scenarios – Baseline, Adverse and Severely Adverse

Thresholds for Breach

- BHCs are expected to maintain a minimum common equity tier-1 capital ratio of 4.5 under all supervisory scenarios

Outlier Banks

- Banks that breach minimum capital ratios would face ban on capital raising and distribution, severe fines & operational restrictions.

Case study 2: Capital modelling and stress testing

Project Capital Ratios for each participating BHC – Severely adverse scenario

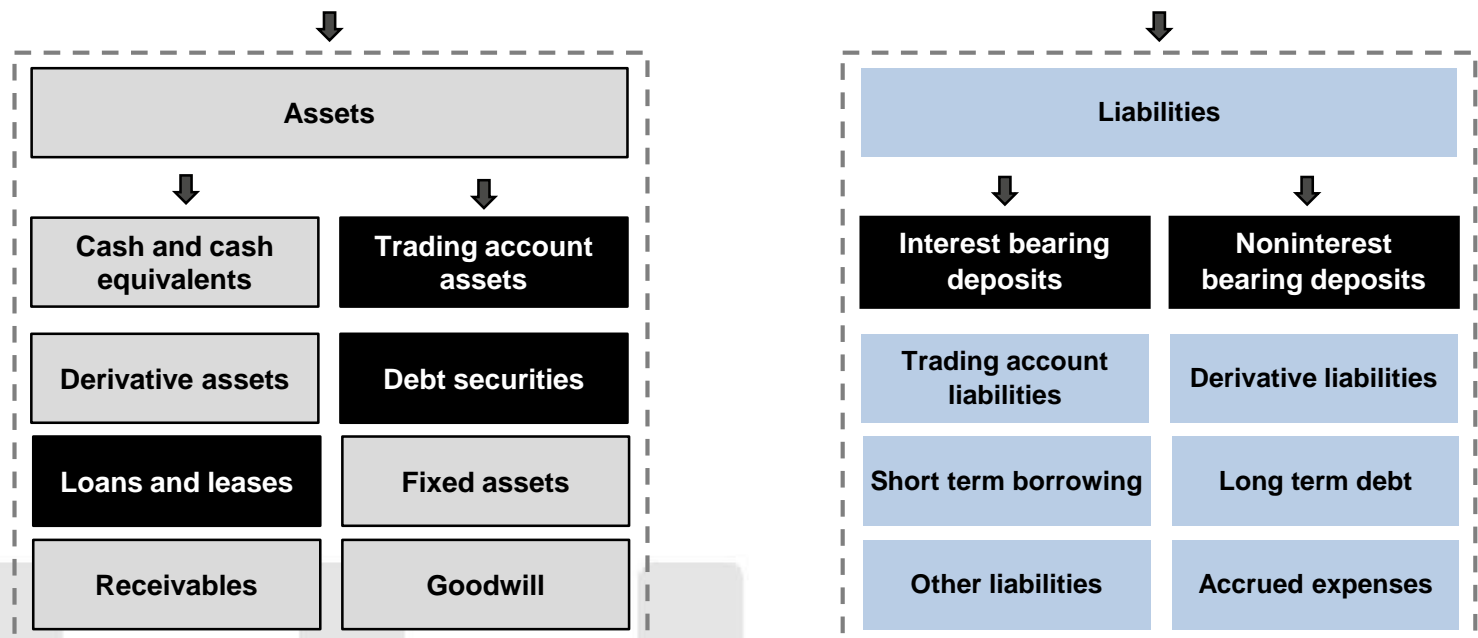
Table 6. Projected minimum regulatory capital ratios in the severely adverse scenario, 2019:Q1 to 2021:Q1: 18 Participating Firms
Percent

Firm	Capital actions	Common equity tier 1 capital ratio		Tier 1 capital ratio		Total capital ratio		Tier 1 leverage ratio		Supplementary leverage ratio ¹	
		Actual 2018:Q4	Projected minimum	Actual 2018:Q4	Projected minimum	Actual 2018:Q4	Projected minimum	Actual 2018:Q4	Projected minimum	Actual 2018:Q4	Projected minimum
Bank of America Corporation	Original	11.6	5.6	13.2	7.1	15.4	9.4	8.4	4.5	6.8	3.7
	Adjusted										
The Bank of New York Mellon Corporation	Original	11.7	8.2	14.1	10.5	15.1	11.6	6.6	4.9	6.0	4.5
	Adjusted										
Barclays US LLC	Original	14.5	11.1	17.6	14.0	21.0	16.1	8.9	7.2	7.3	5.9
	Adjusted										
Capital One Financial Corporation	Original	11.2	3.9	12.7	5.5	15.1	7.7	10.7	4.8	9.0	4.0
	Adjusted	11.2	4.6	12.7	6.2	15.1	8.4	10.7	5.4	9.0	4.6
Citigroup Inc.	Original	11.9	6.9	13.5	8.4	16.6	11.2	8.3	5.2	6.4	4.0
	Adjusted										
Credit Suisse Holdings (USA), Inc.	Original	25.8	16.2	26.5	17.0	26.6	17.1	12.9	7.5	11.3	6.5
	Adjusted										
DB USA Corporation	Original	22.9	14.8	34.4	26.2	34.4	26.6	9.2	6.9	8.4	6.3
	Adjusted										
The Goldman Sachs Group, Inc.	Original	13.3	6.7	15.3	8.6	18.0	11.5	8.9	5.0	6.2	3.5
	Adjusted										
HSBC North America Holdings Inc.	Original	12.6	6.8	14.2	8.4	18.0	11.7	7.5	4.3	5.6	3.2
	Adjusted										
JPMorgan Chase & Co.	Original	12.0	4.4	13.7	6.3	15.5	8.3	8.1	3.8	6.4	3.0
	Adjusted	12.0	4.6	13.7	6.8	15.5	8.7	8.1	4.0	6.4	3.2
Morgan Stanley	Original	16.9	7.7	19.2	10.0	21.8	12.5	8.4	4.4	6.5	3.4
	Adjusted										
Northern Trust Corporation	Original	12.9	9.0	14.1	10.3	16.1	12.3	8.0	5.8	7.0	5.1
	Adjusted										
The PNC Financial Services Group, Inc.	Original	9.6	5.8	10.8	7.3	13.0	9.6	9.4	6.3	7.8	5.3
	Adjusted										
State Street Corporation	Original	11.7	8.2	15.5	11.8	16.3	12.5	7.2	5.5	6.3	4.8
	Adjusted										
TD Group US Holdings LLC	Original	16.3	12.4	16.3	12.4	17.3	13.6	9.2	7.1	8.3	6.4
	Adjusted										
UBS Americas Holding LLC	Original	21.7	11.0	25.7	16.6	27.0	18.6	11.3	7.2	n/a	n/a
	Adjusted									n/a	n/a
U.S. Bancorp	Original	9.1	6.5	10.7	8.2	12.6	10.4	9.0	7.0	7.2	5.6
	Adjusted										
Wells Fargo & Company	Original	11.7	7.0	13.5	8.6	16.6	11.7	9.1	5.8	7.7	4.9
	Adjusted										

Case study 2: Capital modelling and stress testing

A large US based BHC – XYZ, with consolidated assets more than \$100 billion is preparing to submit their forward-looking capital action plan for the upcoming CCAR & DFAST cycle. The bank has used an inventory of more than 500 models to compute capital ratios under each of the supervisory scenarios.

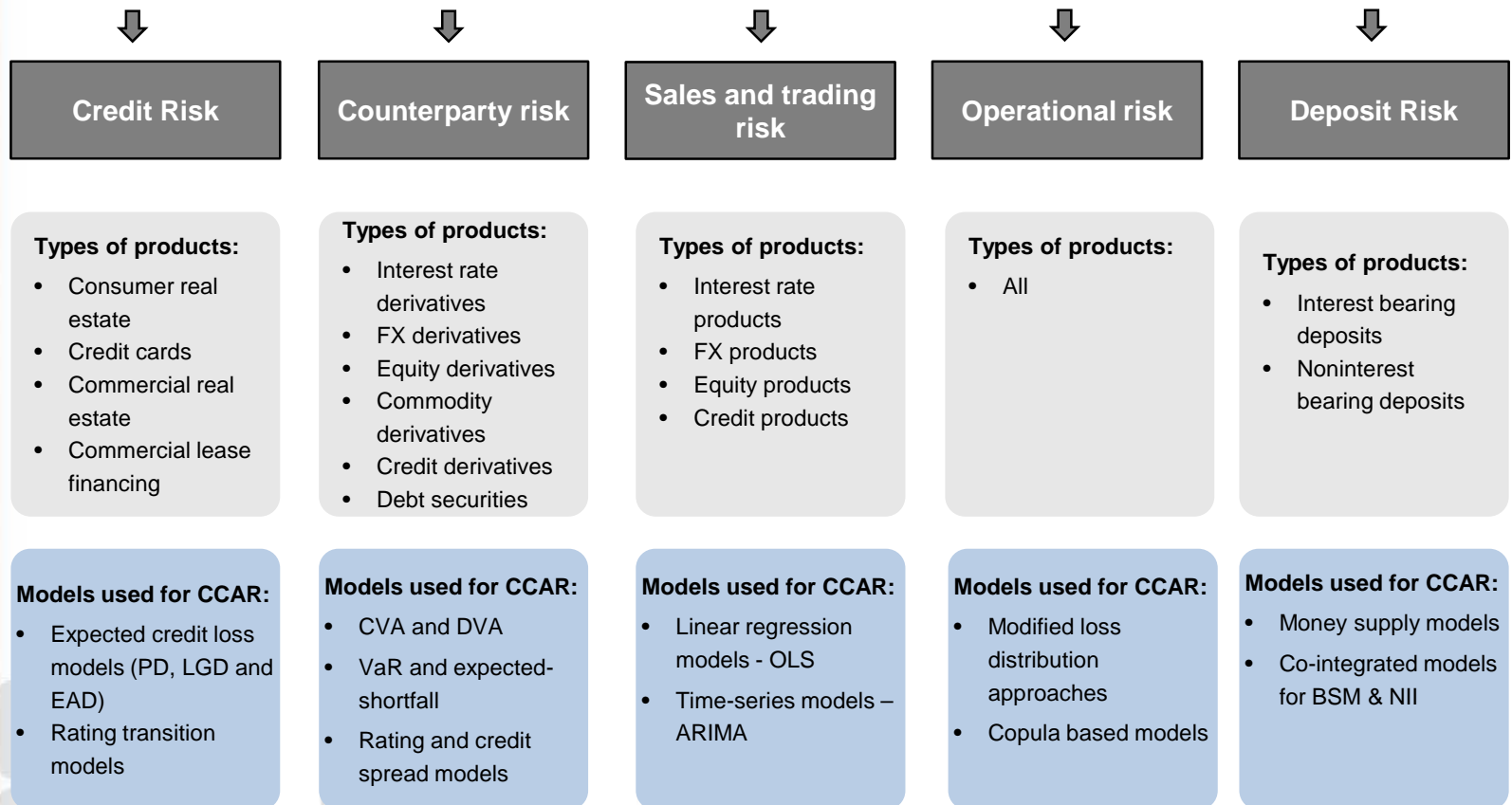
Overview of XYZ's portfolio



■ Line items with exposures more than \$200,000 million

Case study 2: Capital modelling and stress testing

Major exposures in XYZs portfolio arising out of specific products were captured using specific models



Case study 2: Capital modelling and stress testing

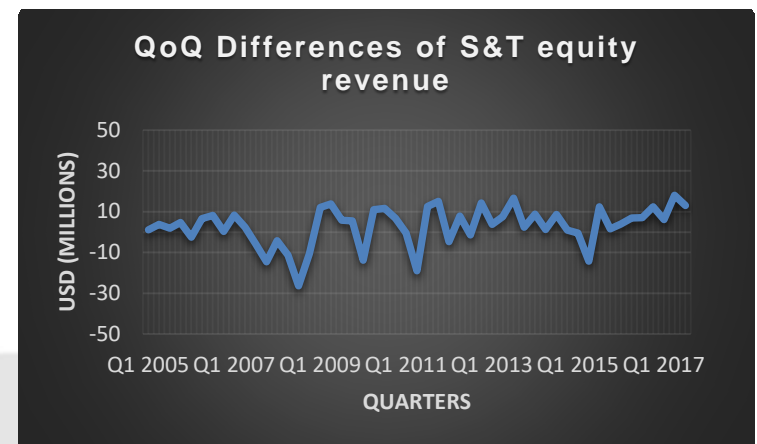
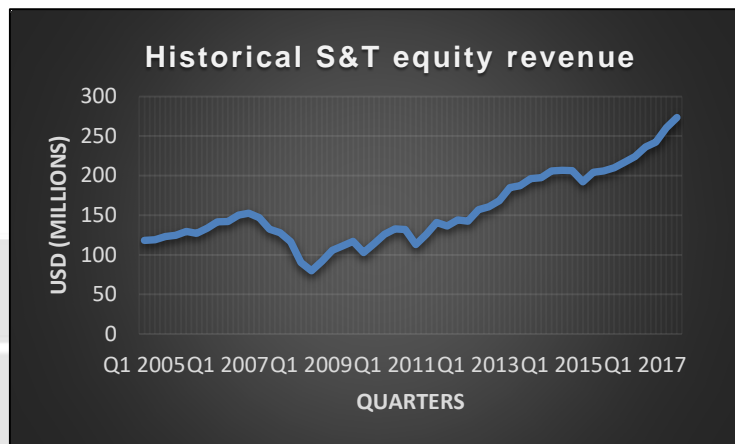
As part of this case study, we would be going through the end to end model development process followed by XYZ for a single PPNR model used to project sales and trading revenues pertaining to the equity asset class



Historical time-series of the sales and trading revenue from the equity asset class



Quarterly differences computed using the historical time-series of the raw dependent variable



Case study 2: Capital modelling and stress testing

Use qualitative and quantitative analysis for variable selection



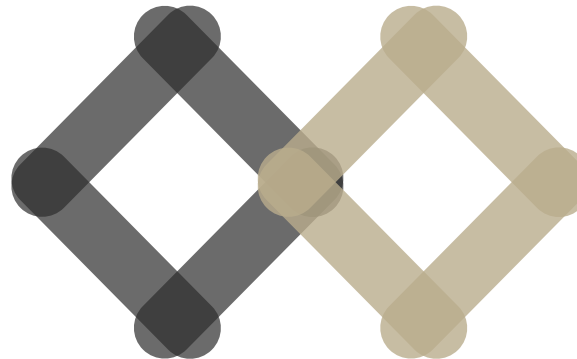
Create repository of independent variables

Productivity & Income

- U.S. Real GDP growth
- U.S. nominal GDP growth

Unemployment & Inflation

- U.S. unemployment rate
- U.S. CPI inflation:
- U.S. nominal disposable income growth
- Euro Inflation



Financial Markets

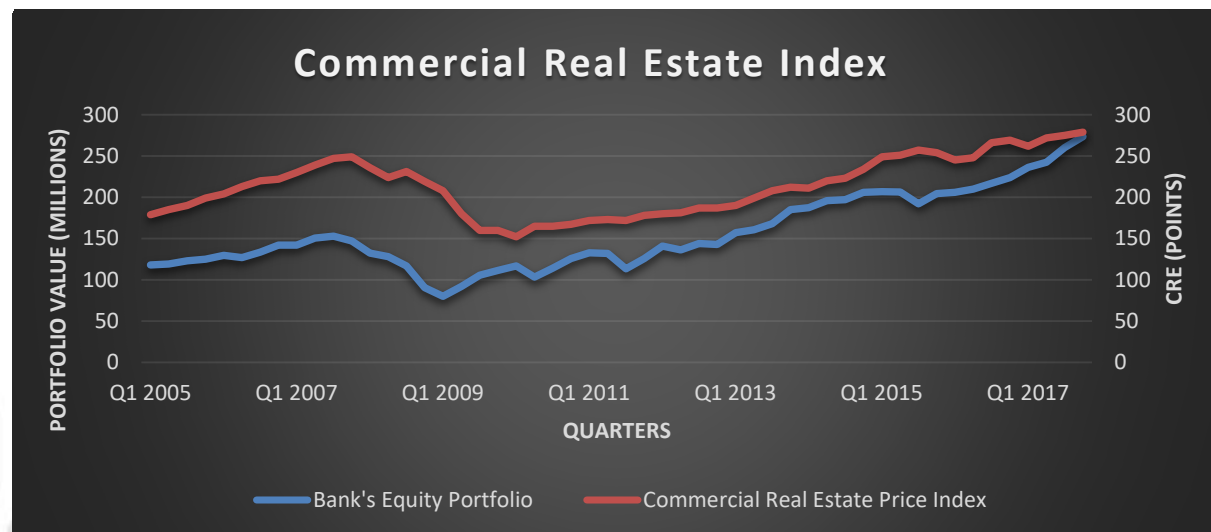
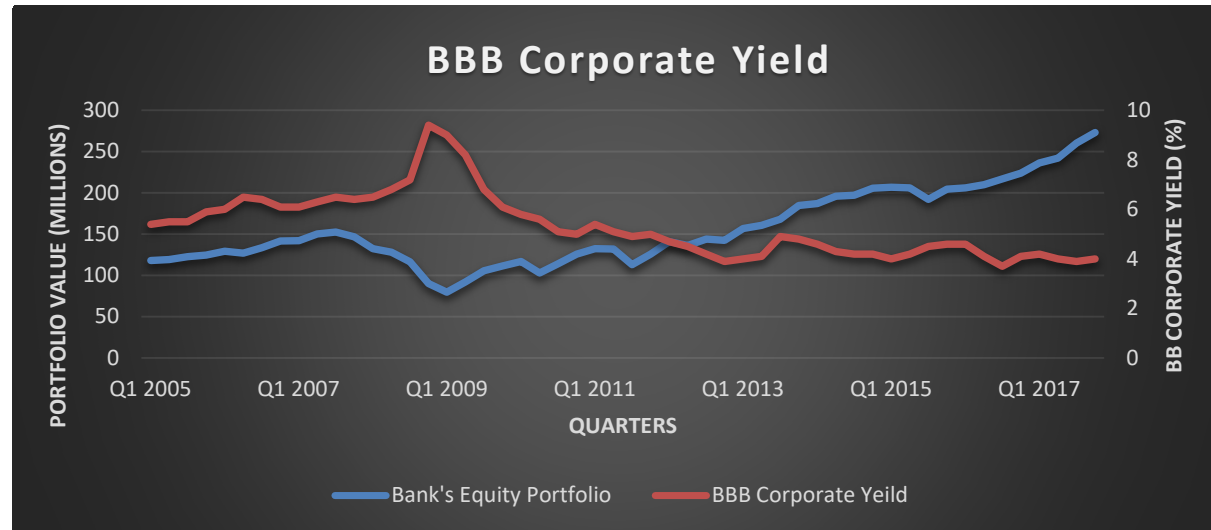
- U.S. 3-month Treasury rate
- U.S. BBB corporate yield
- Money Supply

Indices

- S&P 500 and Dow Jones
- Commercial Real Estate Index
- Market Volatility Index (VIX)

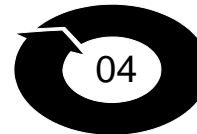
Macro-Economic Variables	Intuitive Economic Relationship	Correlation
BBB Corporate Yield	Inverse	-72.50%
Commercial Real Estate Price Index	Direct	78.26%
Money Supply	Direct	85.82%
Consumer Confidence Index	Direct	80.83%
Business Confidence Index	Direct	63.48%
USD/EURO	Inverse	-61.54%

Case study 2: Capital modelling and stress testing



Case study 2: Capital modelling and stress testing

After identification of independent variables with the highest explanatory power and economic intuition, we proceed towards model estimation. OLS is a common estimation framework used for PPNR models.



Model Calibration

Model Equation

$$\text{EquityPortfolio}_t = \alpha + \beta_1 * \ln(\text{CRE}_t) + \beta_2 * \ln(\text{BBBCorpYield}_t) + \varepsilon_t$$

where:

α is the Intercept

β_1 is the regression coefficient of Commercial Real Estate Index

β_2 is the regression coefficient of BBB Corporate Yield

ε_i are residual errors (Actual – Predicted)

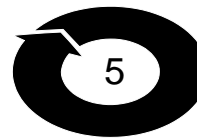
Economically intuitive
model coefficients

Post-Calibration Results

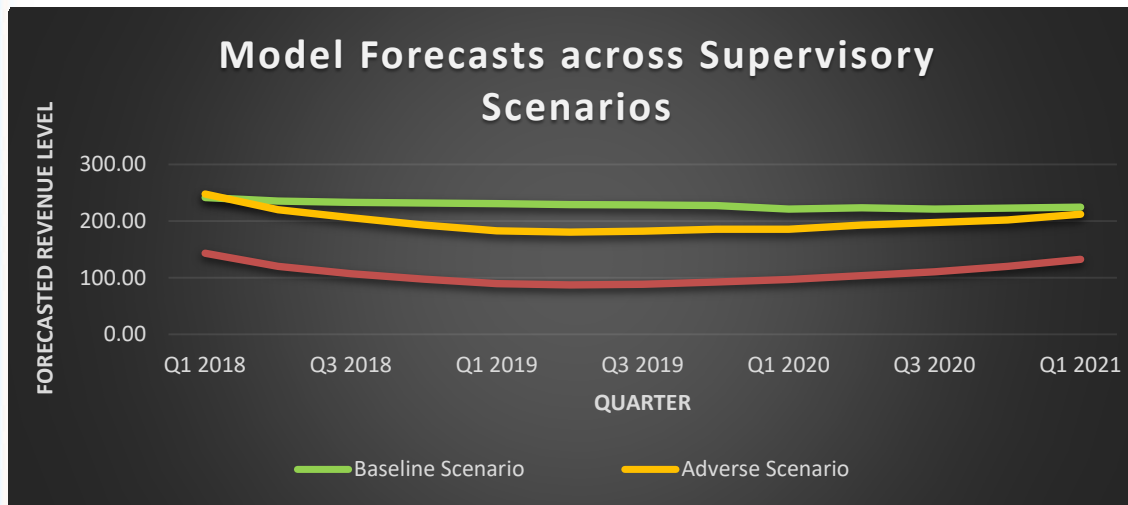
Parameter	Coefficients	Standard Error	T-Stat	P-value
Intercept	3.4451	0.3977	8.6625	< 0.0001
Log Transformed CRE	0.9744	0.0686	14.2132	< 0.0001
Log Transformed BBB Corporate Yield	-0.8172	0.0507	-16.1039	< 0.0001

Case study 2: Capital modelling and stress testing

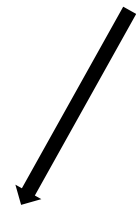
Generate stress projections for CCAR & DFAST using projections of chosen independent variable as an input to the estimated model framework



Generate stress projections for CCAR



Model generates economically intuitive stress forecasts

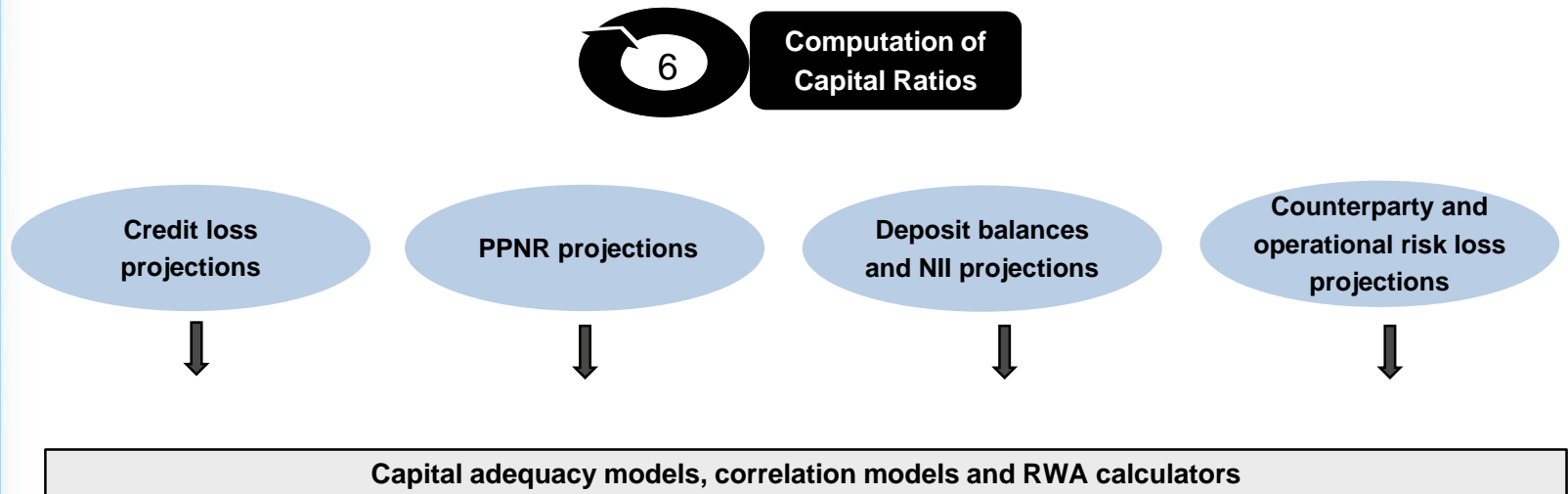


Expected 9Q Loss Under Each Scenario (Millions)			
Initial Revenue Level (Q4 2017)	Baseline Scenario	Adverse Scenario	Severely Adverse Scenario
273.35	5.18	8.78	17.63

Case study 2: Capital modelling and stress testing

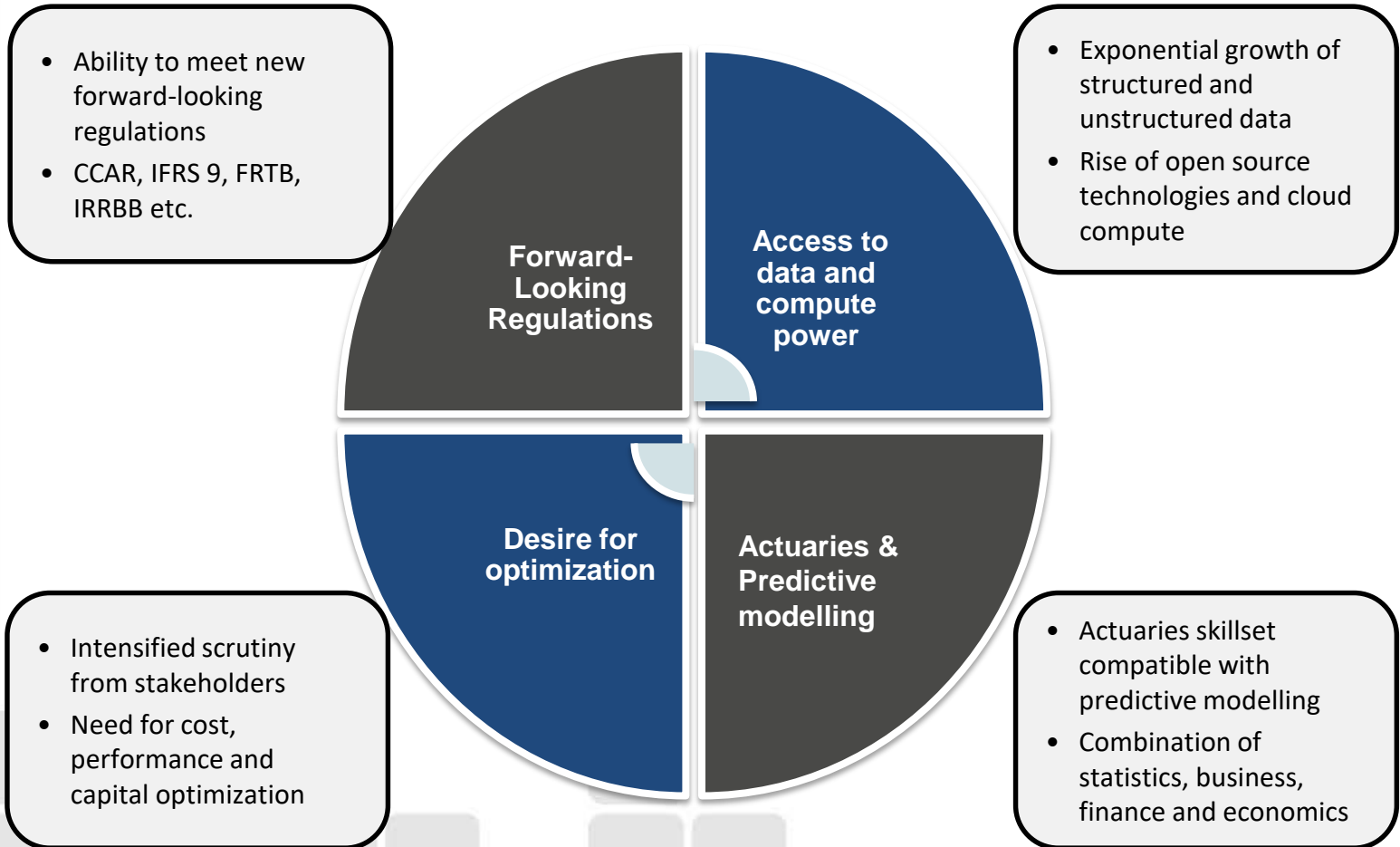


Stress projections generated by a diverse set of models covering different items of XYZs balance sheet – Credit losses, PPNR, operational risk losses, balances etc. are aggregated to compute required capital and leverage ratios for CCAR & DFAST compliance



Projected regulatory capital and leverage ratios				
Regulatory Ratio	Actual	Adverse Scenario (Minimum Ratios)	Severely Adverse Scenario (Minimum Ratios)	Minimum Ratio Threshold
Common equity tier 1 ratio	10.4	7.5	4.4	4.5
Tier 1 capital ratio	12.8	8.7	6.9	6.0
Total capital ratio	13.3	10.9	9.1	8.0
Tier 1 leverage ratio	8.1	5.5	3.9	4.0
Supplementary leverage ratio	6.4	4.6	3.5	3.0

Key-Takeways

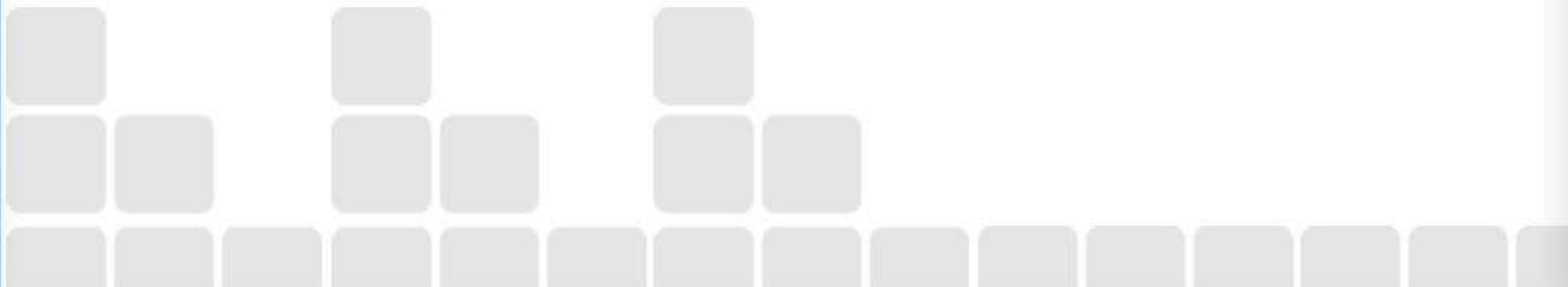


Q/A



Questions ?

Comments



Thank You

Application of predictive models in the banking industry

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