Credit Scoring for Basel II

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Union Bank

Why Basel II?

Union Bank is opting in to adopt Basel II standards for a variety of reasons:

Former CEO Masa Tanaka on Basel II:

Adopting Basel II "… will allow us to use our own internal models for measuring credit and operational risk to meet regulatory capital requirements (. . .) under Basel II, banks that take less risk and incur fewer losses over time are allowed to set aside less regulatory capital. With lower risks we can expect substantial capital savings compared to banks that have decided not to opt in under Basel II or those that did opt in but had riskier portfolios."

Investment in Basel II can lead to:

- Better portfolio management with access to more timely and accurate information on changes affecting risk
- Better business decisions with more accurate measurement of economic capital and risk-adjusted returns
- Fewer resources committed to manual data entry, remediation, aggregation, and reporting

(Connections, July 25, 2008)

BASEL II Overview – Minimum Capital Charge

- The Basel Accord is structured in three mutually reinforcing sections or "Pillars":
  - **Pillar I – calculation of minimum regulatory capital**
  - Pillar II – supervisory review of overall regulatory capital adequacy as determined by the bank
  - Pillar III – disclosure to the market of risk and capital information
- For Advanced-IRB retail portfolios the capital requirement is determined by a complex mathematical formula that uses Probability of Default (PD), Exposure at Default (EAD) and Loss Given Default (LGD) as inputs. It is NONLINEAR and based on Asymptotic Single Risk Factor (ASRF) assumption. This differs from Expected Credit Loss (PD * LGD * EAD).
- The formula will vary according to the following asset types:
  - Retail (Mortgages, Qualifying Revolving Exposures (QRE), Other retail)
  - Banks determine the following input parameters: PD, LGD and EAD

$$\text{Minimum Regulatory Capital} = \text{EAD} * \text{LGD} * f\,(\text{PD}, \text{AVC})$$

Exposure at Default: an estimate of the amount the borrower would owe the Bank at default.

Loss Given Default: an estimate of percentage of the EAD that the Bank would expect to lose in the event of a borrower default.

The Basel II formula specifies the shape of the unexpected loss curve (Based on ASRF assumption)

Probability of default: the likelihood of a borrower defaulting on an obligation over a 12-month period.

Asset Value Correlation (AVC): the correlation of assets among themselves (non-diversifiable risk). This varies between assets.

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Overview of work leading up to 'parallel run'

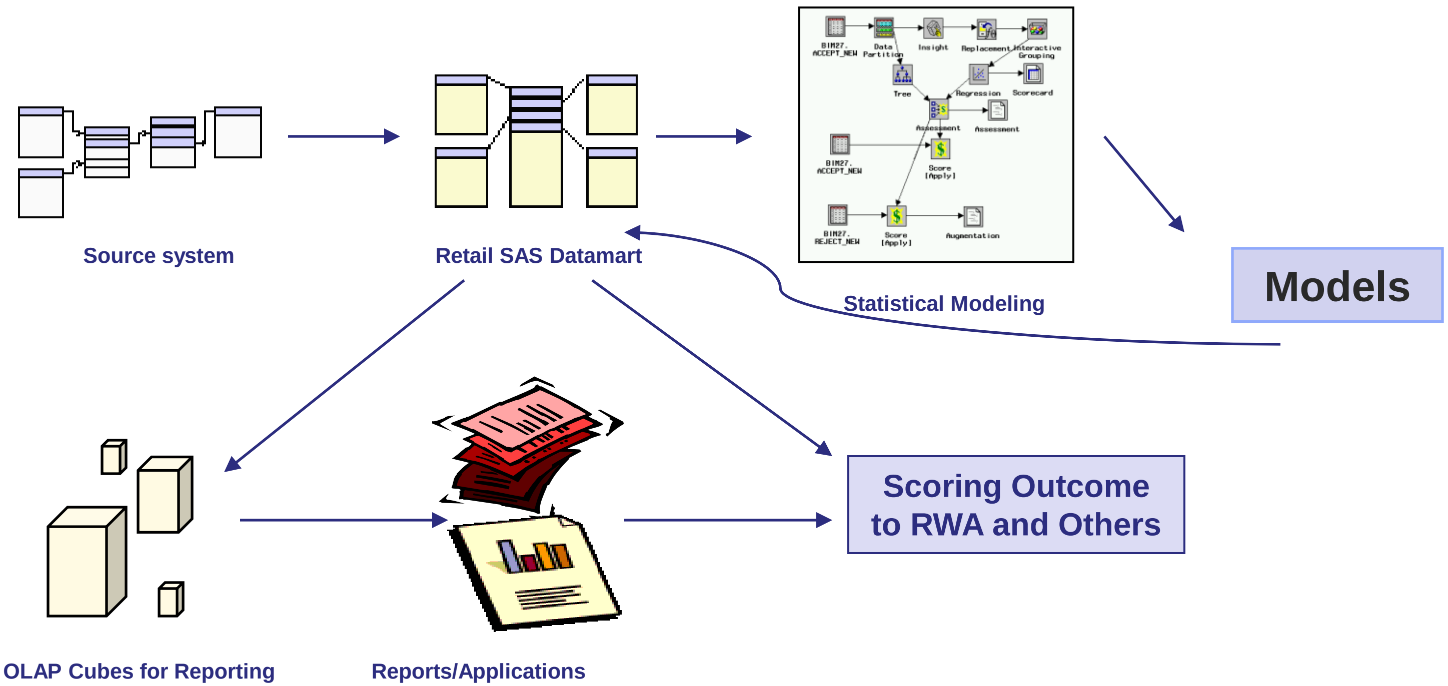
2008-2009:

- Ensured data sufficiency per Basel II data requirements
  - Researched internal portfolio historical data
  - Built prototype models
- Purchased and installed SAS Credit Scoring for Banking Solution software for model building and implementation
- Built production SAS datamart in the SAS Production Platform

2010-2011:

- Built PD, LGD, EAD models and segmentation calculation for all portfolios
- Completed independent validation of Mortgage and Home Equity models
- Completed formal OCC Review May 2010
- Designed Basel II results download process for the RWA calculation
- Scored monthly 'live' data starting end of June 2010
- Annual model update in early 2011

Basel II Retail SAS Production Platform

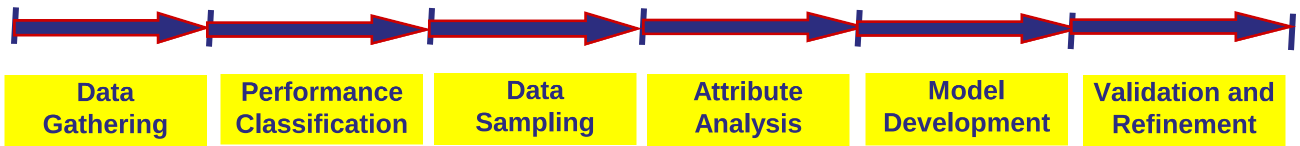


The SAS Production Platform Can:

- Host historical and ongoing retail portfolio data
- Develop, register, and deploy statistical models
- Create automated and ad hoc reports
- Perform model validation, benchmarking, and ongoing model performance monitoring
- Create and deliver data to other data environment for various business purposes (e.g., RWA and ITG-DI environment)

PD, LGD, and EAD Modeling Methodology

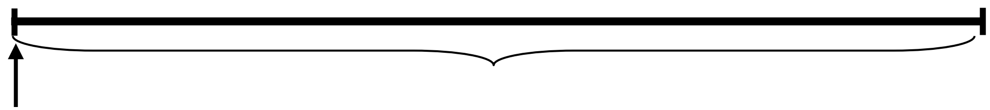
- The model building process follows several steps:



- Data Gathering
  - Extracted historical loan origination, account management information to search insights about the customers
- Performance Classification
  - Probability of Default (PD)
    - Charged off or partial charge off or
    - Mortgage and Home Equity: 180 days past due, or
    - Other Retail Exposures: 120 days past due or charged off
  - Loss Given Default (LGD)
  - Exposure at Default (EAD)

PD, LGD, and EAD Modeling Methodology (continued)

- **Create Data Samples for Model building**
  - Create 1 Year cohorts of observation (minimum 5 years)
  - 12-months performance period following the observation month



- **Attribute Analysis**
  - Apply variable combinations and transformations to ensure optimal model development
- **Model Development**
  - Use 70% of the data sample as development sample
  - Use 30% of the data sample as validation sample
- **Model Validation and Refinement**
  - Reiterate the model development and validation process to ensure optimal model outcome
  - Revolving Validation Method
  - Out of Time Validation Method

Probability of Default Methodology

Application Characteristics

- FICO / Credit Score
- Mortgage type
- Time till int. rt. reset
- Origination LTV
- Co-borrower indicator

Behavior Characteristics

- Refreshed FICO / Credit Score
- Borrower behavior / payment history
- Time till int. rt. reset
- Utilization rate
- Month on book
- Delinquency status
- Adjusted LTV

Origination Model
(Loan Age < 6 Months)

Current Model
(< 30 DPD Segment)

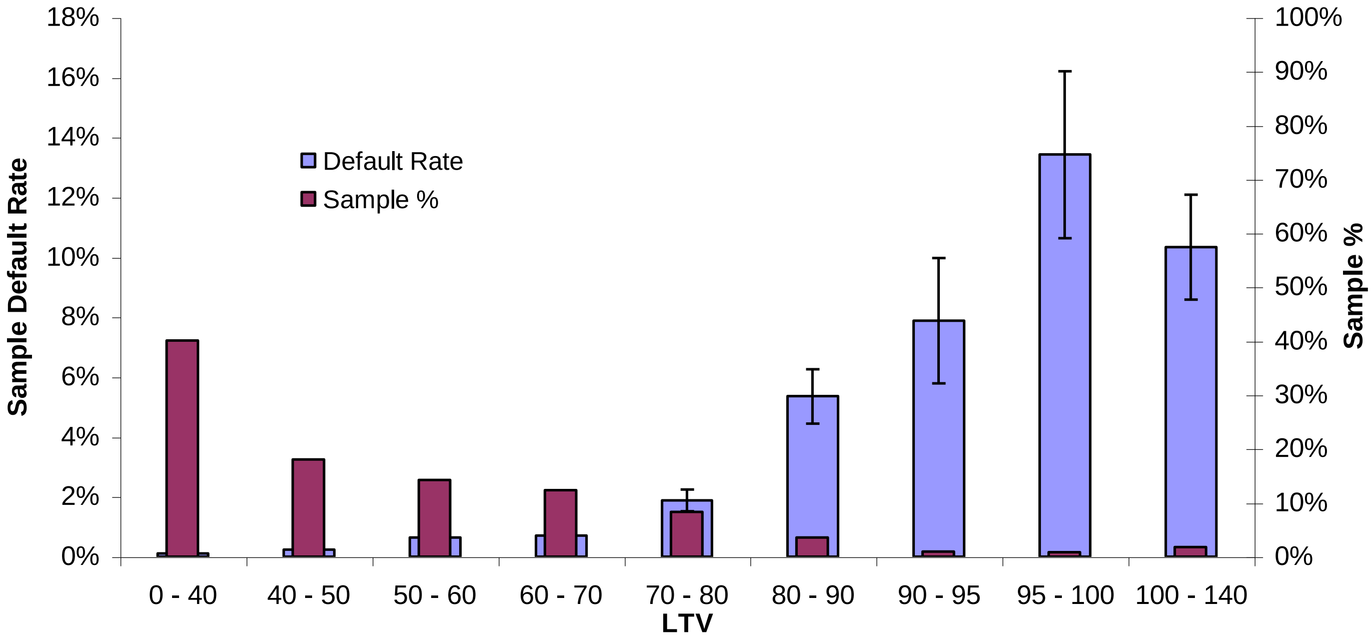
Indeterminate Model
(30 - 179 DPD Segment)

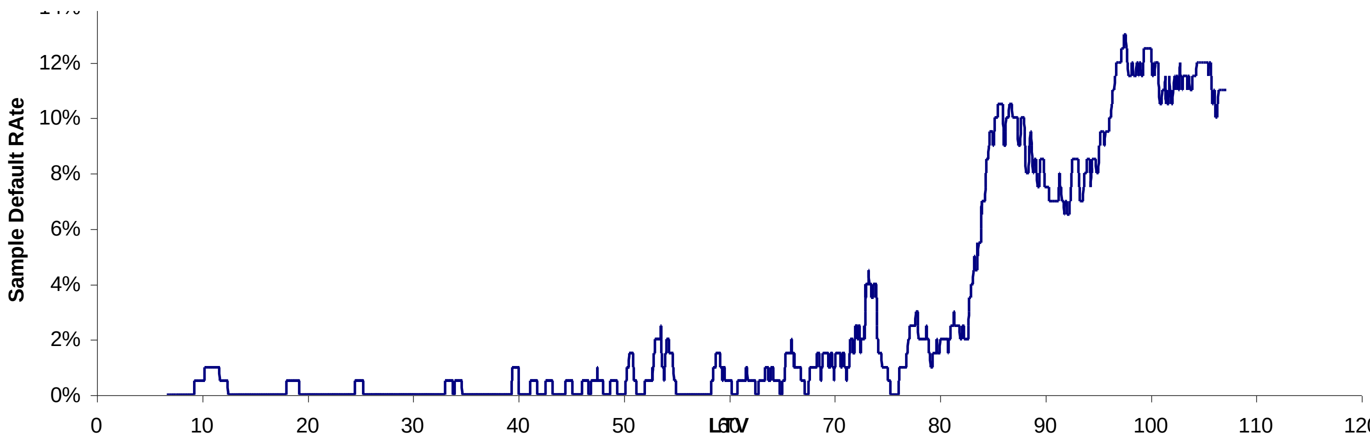
Loan Level Predicted PD

PD Segmentation Model
(based on segment-level historical default rates)

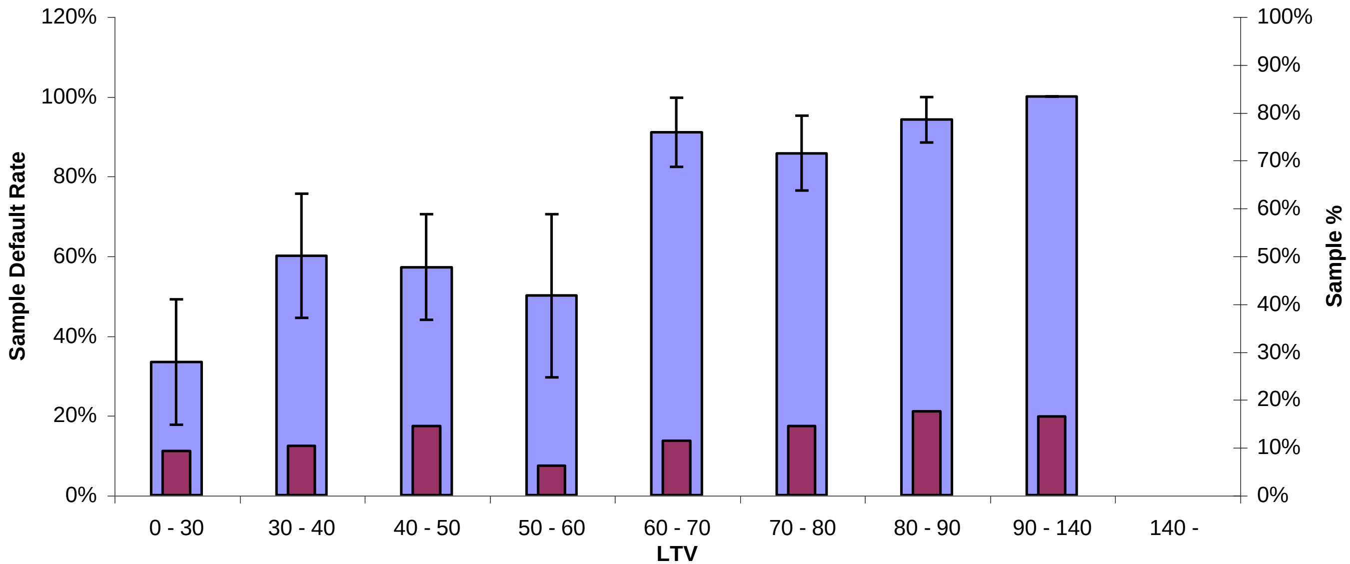
PD estimates by segment

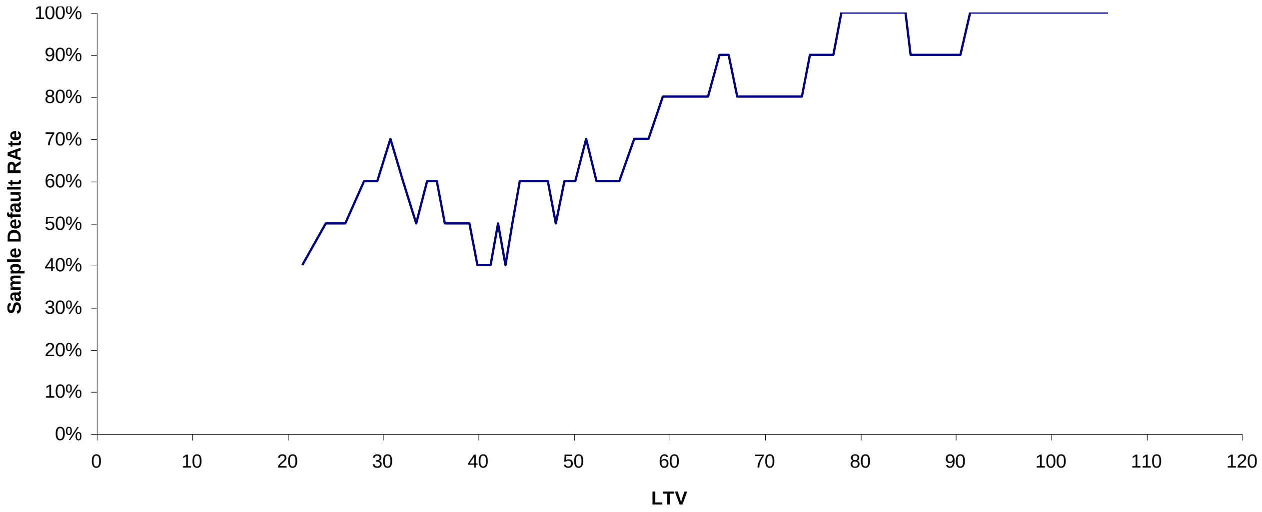
Variable transformation – Case/Shiller adjusted LTV





Variable transformation – Case/Shiller adjusted LTV, Indeterminates (30-179 days past due)





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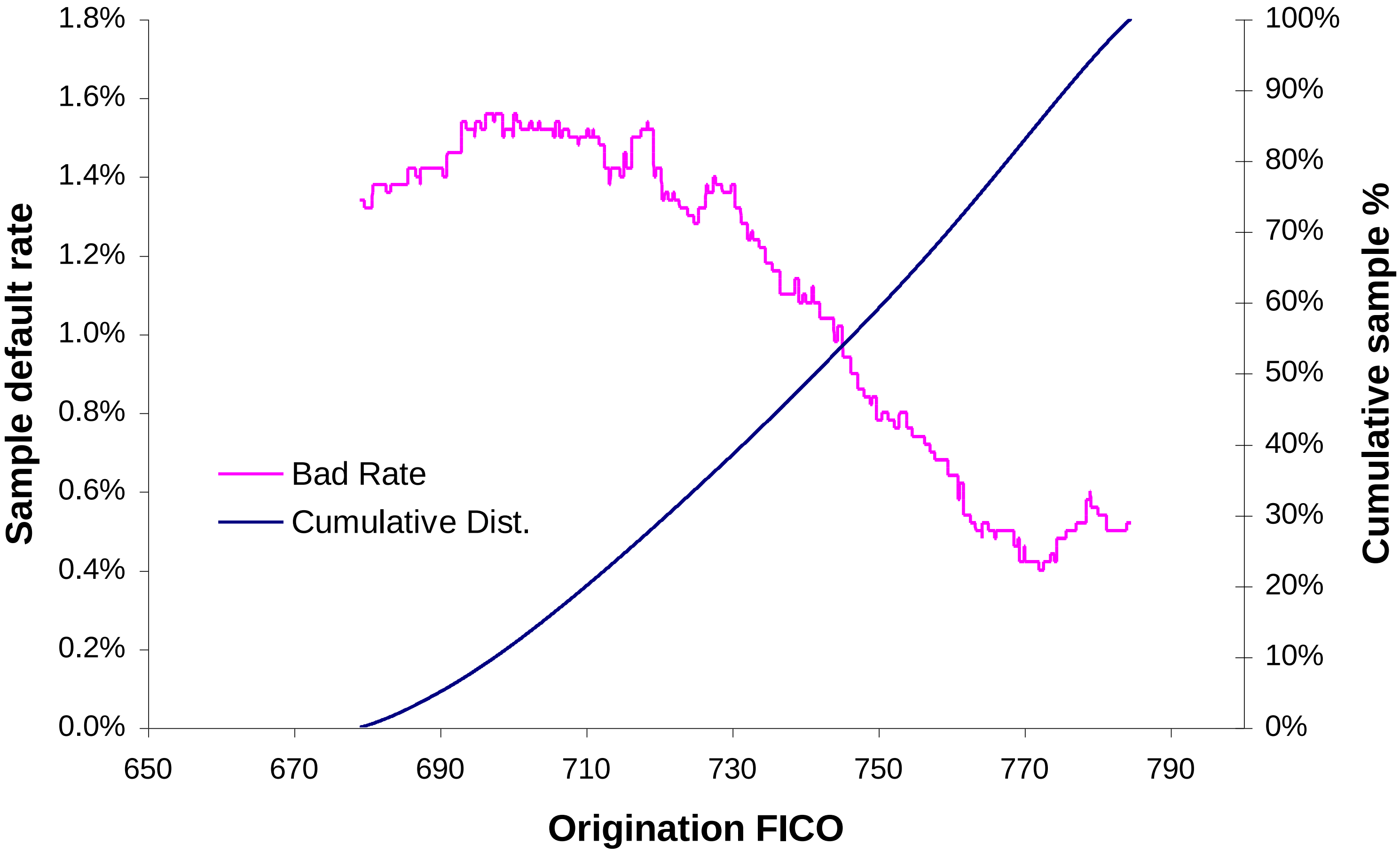
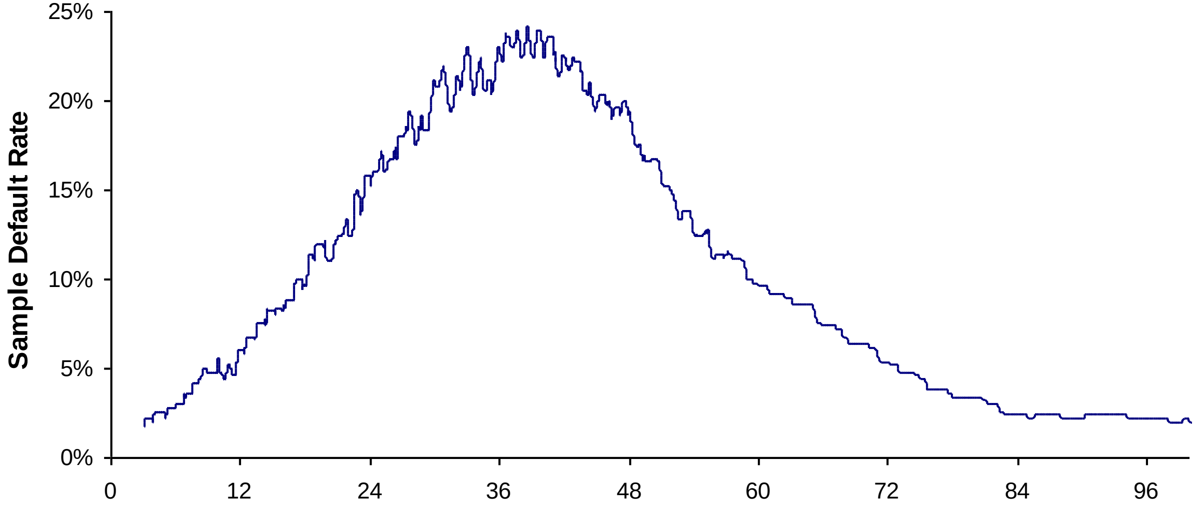
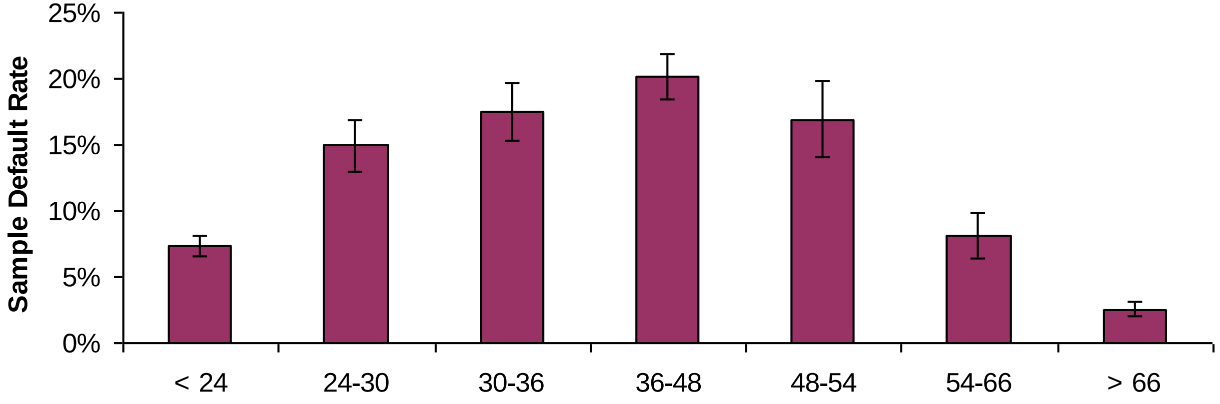
Variable transformation - FICO



Variable transformation – Months on Book





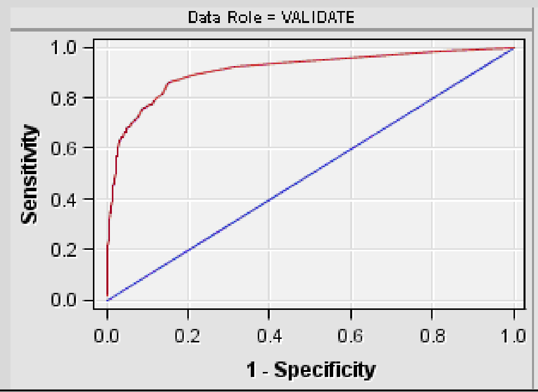
Probability of Default Result and Model Fit

Mortgage and Home Equity PD models were estimated based on Weights of Evidence transformation of the risk drivers. The selected risk drivers and the corresponding weights in the production models are shown on the left. The model fit assessment by ROC curve and index are shown on the right:

Current Model

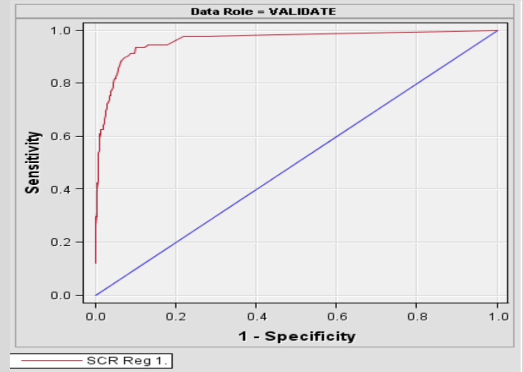
Portfolio	Input Variable	Relative Weight
MTG	Refreshed FICO Score	43%
	Case Shiller Adjusted LTV	33%
	Time Until Interest Rate Reset	13%
	Months on Book	12%
HE	Case Shiller Adjusted CLTV	33%
	Flex Product Utilization	22%
	Refreshed FICO Score	16%
	# Times 30-59 DPD	8%
	Months on Book	7%
	Maximum # Days Delinquent	7%
	# Non-sufficient fund Reversals	6%

Mortgage



ROC Index	0.91

Home Equity



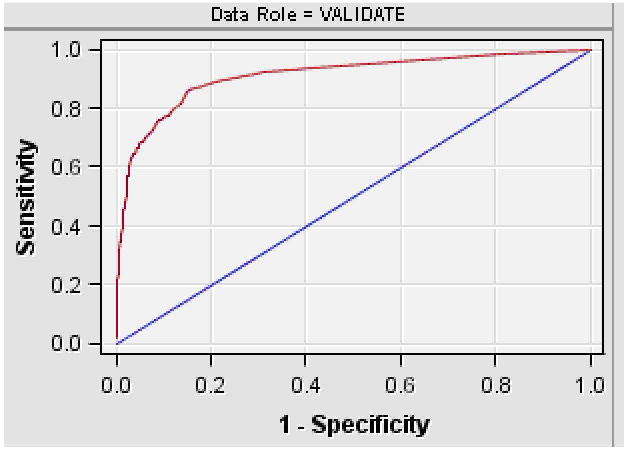
ROC Index	0.96

Predictive power backtesting

Additional Out-of-Sample Validation

Input Variable	AB	AC	BC
Intercept Case Shiller Adjusted LTV Refreshed FICO Score Month on Books Time Until Interest Rate Reset			
Measure	**AB**	**AC**	**BC**
ROC KS	0.93 0.74	0.92 0.73	0.91 0.71

ROC curve (Validation)



Measure	Train	Validate
ROC	0.92	0.91
KS	0.73	0.71

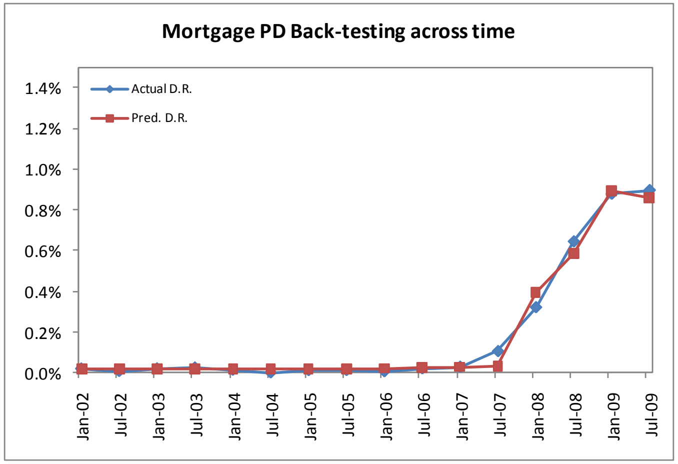
Split between training sample (70%) and validation sample (30%)

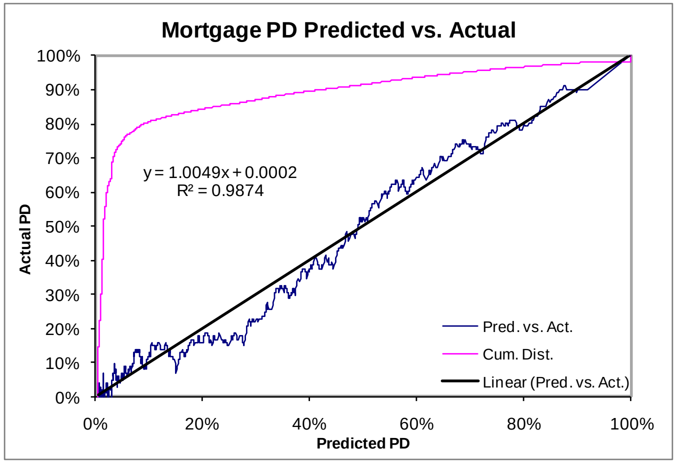
Additional Out-of-Time Validation

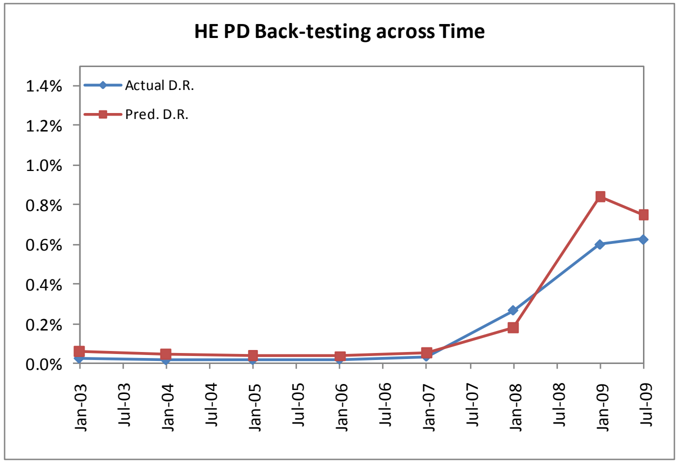
Input Variable	Build on 2002-2008 Validate on 2009	Build on 2009 Validate on 2002-2008
Intercept Case Shiller Adjusted LTV Refreshed FICO Score Month on Books Time Until Interest Rate Reset		
Measure	**Build on 2002-2008 Validate on 2009**	**Build on 2009 Validate on 2002-2008**
ROC KS	0.85 0.60	0.89 0.67

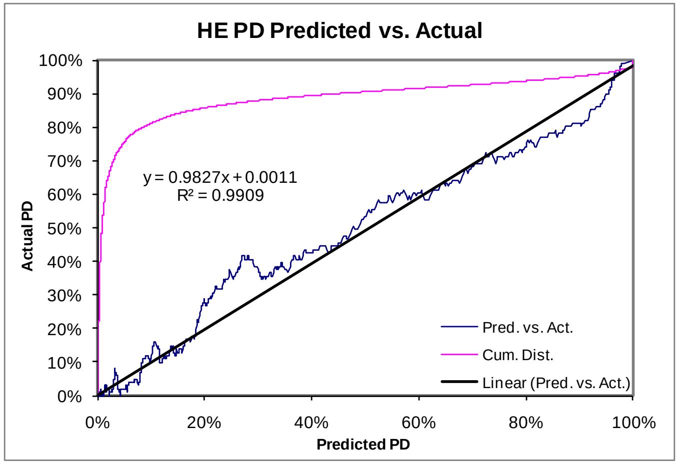
Predictive accuracy back-testing

Besides fit assessment of the PD models, back-testing is another important and necessary assessment of the models' predictive power and accuracy. The basic idea of back-testing is to examine how "closely" the prediction of PD tracks the actual historical default rate across different dimensions.









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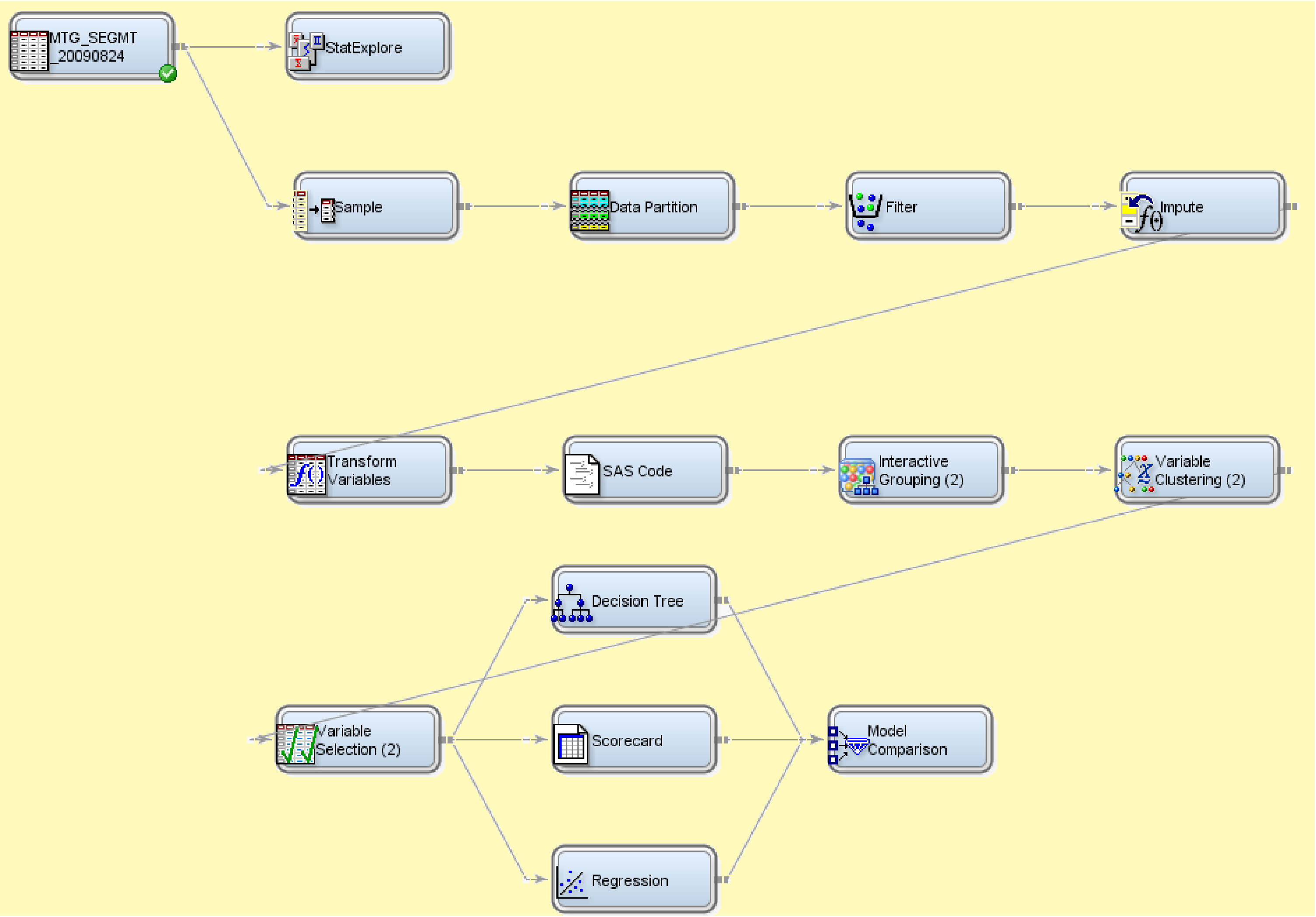
SAS Enterprise-Miner Example



SAS E-Miner

Different nodes in the E-Miner allows you to:

- Explore the data
- Perform statistical analysis
- Treat missing values
- Transform variables
- Group variables with similar characteristics
- Build multiple statistical models
- Compare model outcome using validation data
- Select the best model
- Package the final model for deployment

Loss Given Default Methodology

- **Loss Give Default (LGD):** notion of "**economic loss**" which should capture all material credit-related losses on the exposure (including accrued but unpaid interest or fees, losses on the sale of repossessed collateral, direct workout costs and an appropriate allocation of indirect workout costs), on a net present value basis as of the default date using a discount rate appropriate to the risk of the exposure

$$LGD = \frac{Loss\ (including\ fees\ and\ interest) + Workout\ Costs}{EAD}$$

where

$$EAD = Balance\ Unpaid + Interest\ Unpaid + Fees\ Unpaid + LateCharge\ Unpaid$$

and the net loss is calculated based on the following components:

Loss / Recovery Component	Unresolved Properties	Resolved Properties
Balance, Fees and Interest	X	X
Charge-off Principal	X	
REO Costs	X	X
REO Principal Writedowns	X	
REO Recoveries	X	X
REO Property Sales		X
Short Sales		X
Paid in Full Events		X
Writedown Report Expected Loss	X	

- LGD Models for both Mortgage and Home Equity were developed on all default accounts January 2002 – January 2009

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Sample LGD data

Transaction level cashflow data for REO portfolio

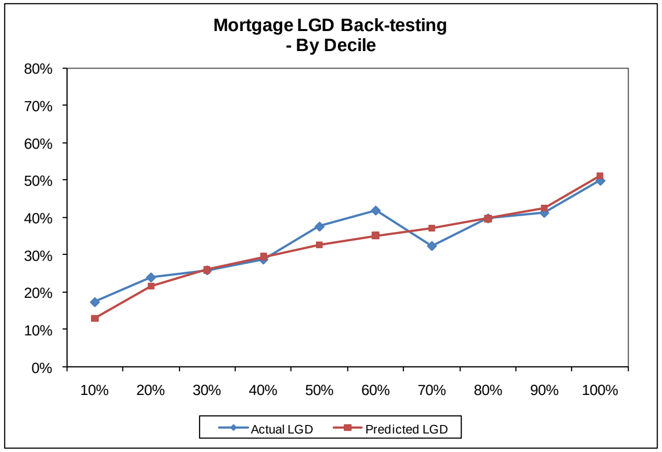
Type	Date	Name	Memo	Debit	Credit
Bill	1/4/2000		Book In Blance	$95,727	
Bill	3/17/2000		Rekey and Secure	$129	
Bill	3/20/2000		99/2000 2nd Installment	$386	
Bill	4/7/2000		Utilities	$8	
Bill	4/7/2000		Board Windows/Fence	$625	
Bill	4/7/2000		Pest Report	$105	
Bill	4/10/2000		Property Value Writedown	$21,327	
Deposit	4/10/2000		Writedown		$21,327
Bill	4/14/2000		Eviction Proceedings	$1,887	
Bill	4/14/2000		Trashout/Clean	$600	
Bill	4/14/2000		Yard Maintenance	$150	
Bill	4/14/2000		Alarms and Straps	$155	
Bill	4/14/2000		Wash and Belach Mold from Walls	$225	
Bill	4/14/2000		Remove Carpet and Haul to Dump	$250	
Bill	4/19/2000		trashout int. & ext. cleanup of property, remove carpet/hual, strap w/h, install smoke dect.	$1,380	
Bill	4/24/2000		electric bill	$4	
Bill	5/19/2000		Water	$166	
Bill	5/19/2000		Yard Maintenance	$100	
Bill	6/15/2000			$4	
Bill	6/20/2000		Utilities	$79	
Deposit	6/27/2000		Sale Price $75000		$74,400
Deposit	6/27/2000		Sale Price $75,000		$615
Bill	7/24/2000			$100	
Bill	7/24/2000			$100	
Bill	7/24/2000			$7	
Bill	3/1/2001		1999 SUPPLEMENTAL ASSESSMENT	$127	

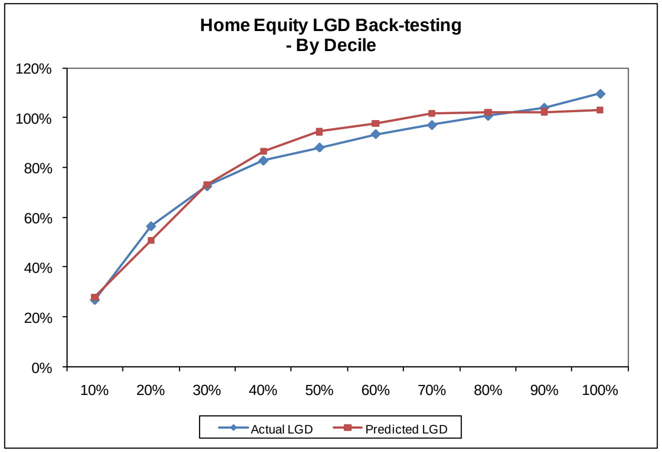
Loss Given Default Result and Back-testing

LGD was estimated by a hybrid approach: calculate segment level account weighted LGD based on estimated loan level. The selected risk drivers and the corresponding weights in the production models are shown on the left. The model back-testing across time results are shown on the right:

Loan - level Model

Portfolio	Input Variable	Relative Weight
MTG	Months on Book	32%
	Loan Balance	29%
	Case Shiller Adjusted LTV	26%
	Fix Rate Indicator	13%
HE	Case Shiller Adjusted CLTV	50%
	First Lien Indicator	29%
	Months on Book	26%
	Current Commitment	13%





Mortgage segmentation

Segment ID	PD Segment	DPD	LGD Segment	# Accts	Total Balance	Avg PD	Avg LGD	Assigned PD	Assigned LGD	Basel Captial
1	< .04%	< 30 DPD	< 19.5%			0.0%	7.8%	0.03%		
2	.04% - .16%	< 30 DPD	< 19.5%			0.1%	7.0%	0.1%		
3	.16% - .75%	< 30 DPD	< 19.5%			0.4%	6.8%	0.3%		
4	.75% - 2.23%	< 30 DPD	< 19.5%			1.2%	7.3%	1.4%		
5	2.23% - 4.58%	< 30 DPD	< 19.5%			3.0%	6.8%	3.4%	13.6%	
6	> 4.58%	< 30 DPD	< 19.5%			10.8%	7.0%	12.7%		
7	< 5.1%	30-179 DPD	< 19.5%			2.5%	4.4%	2.1%		
8	5.1% - 21.1%	30-179 DPD	< 19.5%			9.9%	6.8%	7.2%		
9	21.1% - 72.5%	30-179 DPD	< 19.5%			43.4%	6.7%	43.1%		
10	>72.5%	30-179 DPD	< 19.5%			89.5%	5.9%	86.5%		
11	< .04%	< 30 DPD	19.5% - 33.2%			0.0%	26.6%	0.03%		
12	.04% - .16%	< 30 DPD	19.5% - 33.2%			0.1%	26.2%	0.1%		
13	.16% - .75%	< 30 DPD	19.5% - 33.2%			0.4%	25.8%	0.3%		
14	.75% - 2.23%	< 30 DPD	19.5% - 33.2%			1.3%	26.3%	1.4%		
15	2.23% - 4.58%	< 30 DPD	19.5% - 33.2%			3.1%	26.8%	3.4%	27.9%	
16	> 4.58%	< 30 DPD	19.5% - 33.2%			9.7%	26.5%	12.7%		
17	< 5.1%	30-179 DPD	19.5% - 33.2%			2.1%	26.3%	2.1%		
18	5.1% - 21.1%	30-179 DPD	19.5% - 33.2%			12.8%	26.8%	7.2%		
19	21.1% - 72.5%	30-179 DPD	19.5% - 33.2%			46.8%	26.9%	43.1%		
20	>72.5%	30-179 DPD	19.5% - 33.2%			88.3%	26.1%	86.5%		
21	< .04%	< 30 DPD	> 33.2%			0.0%	37.1%	0.03%		
22	.04% - .16%	< 30 DPD	> 33.2%			0.1%	39.6%	0.1%		
23	.16% - .75%	< 30 DPD	> 33.2%			0.4%	41.3%	0.3%		
24	.75% - 2.23%	< 30 DPD	> 33.2%			1.3%	41.7%	1.4%		
25	2.23% - 4.58%	< 30 DPD	> 33.2%			3.2%	42.7%	3.4%	39.7%	
26	> 4.58%	< 30 DPD	> 33.2%			10.4%	43.1%	12.7%		
27	< 5.1%	30-179 DPD	> 33.2%			2.5%	35.3%	2.1%		
28	5.1% - 21.1%	30-179 DPD	> 33.2%			12.7%	34.4%	7.2%		
29	21.1% - 72.5%	30-179 DPD	> 33.2%			47.8%	41.8%	43.1%		
30	>72.5%	30-179 DPD	> 33.2%			90.2%	42.3%	86.5%		
31	Default	Default	Default			100.0%	8.0%	100.0%	8%	

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Credit Analytics Applications

Credit Analytics not only can be utilized to estimate minimum regulatory capital and economic capital the bank uses to cushion unexpected losses, but it can also be leveraged by Credit Portfolio Risk Management to optimize risk-reward profile of new originations as well as actively and effectively manage the bank's risk position.

Credit Analytics Applications	"Organic Growth" (New Originations)	Risk-based Decision (Existing Portfolios)
Optimize risk-reward profile by effectively allocating capital across geography, product type, line of business, etc.	●	●
Leverage the data collected and model outputs to analyze risk sensitivity to the business cycle and adjust the Bank's growth strategy as needed	●	
Understand changes in industry behavior and market direction to promptly identify negative trends, allowing for early risk mitigation actions, hedging and dynamic portfolio optimization		●
Leverage risk-adjusted return metric to create customized pricing strategies.	●	
Understand the risk-reward profile of asset classes to drive enterprise-level concentration management, asset allocation strategies and stress testing to mitigate against "one-time large-loss" events that require costly capital raising		●
Leverage the data collected to develop early warning signals that prompt risk mitigation actions		●