

The Economic Value of Credit Rating Systems

Quantifying the Benefits of Improving an Internal Credit Rating System

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Economic Value of Credit Rating Systems

- Poor statistical power in a bank's internal rating system can negatively impact economic performance due to adverse selection.
- Adverse selection occurs when customers with better credit quality than those assessed by the bank leave, leaving behind a portfolio with lower-than-expected credit quality.
- Enhancing the statistical power of a rating system can positively influence economic performance.
- The magnitude of this positive impact depends on the competitiveness of the market environment.
- Investing in rating system improvements entails organizational, IT, and data management expenses. Therefore, comparing the benefits of enhancement against these costs can be valuable for banks.
- The following slides outline a framework for quantifying the benefits of such an investment. For more details on the proposed framework, refer to this [document](#).

Modeling Framework - Key Concepts and Assumptions

The following points outline the main concepts and assumptions of the modeling framework for evaluating the benefits of an improved credit rating system:

- *Statistical Power*: Improved accuracy in estimating individual Probabilities of Default (PD) reduces adverse selection and impacts pricing.
- *Adverse Selection*: Poor rating systems may misprice risk, leading to higher-quality customers leaving and only riskier clients remaining.
- *Market Competitiveness (Customer Elasticity)*: Modeled by the probability that customers switch banks if offered unfavorable credit spreads.
- *Customer Response to Spread Errors*: If overestimated PD results in a high spread, the customer might leave, modeled by elasticity parameter α .

The Loan Pricing Mechanism

Assuming the bank adopts risk-adjusted pricing, the loan pricing mechanism can be outlined as follows:

- 1 The bank must charge an interest rate r to cover all “general” costs unrelated to credit risk and expected losses.
- 2 Credit risk associated with expected losses is accounted for by adding a credit spread s .
- 3 The credit spread depends on the Probability of Default (PD) and the Loss Given Default (LGD) of the individual exposures. The bank receives $1 + r + s$ if no default occurs. If a default occurs, the bank receives $(1 + r + s) \cdot (1 - LGD)$.
- 4 The expected payoff of the loan must equal the risk-free payoff, leading to the equation:

$$1 + r = (1 - PD) \cdot (1 + r + s) + PD \cdot (1 - LGD) \cdot (1 + r + s)$$

- 5 Solving for the credit spread s gives:

$$s = (1 + r) \cdot \frac{PD \cdot LGD}{1 - PD \cdot LGD}$$

The Adverse Selection Concept

Building on the pricing mechanism outlined in the previous slide, the concept of adverse selection can be explained as follows:

- 1 Customers offered a spread that is too high are likely to leave the bank with a probability that depends on the magnitude m of the deviation from the spread corresponding to their true PD. The magnitude of this deviation is defined as:

$$m = s_{estimated} - s_{true} = (1 + r) \cdot \frac{PD_{estimated} \cdot LGD}{1 - PD_{estimated} \cdot LGD} - (1 + r) \cdot \frac{PD_{true} \cdot LGD}{1 - PD_{true} \cdot LGD}$$

- 2 Assuming $PD_{estimated}$ is available with a given measurement error σ , it is defined as:

$$PD_{estimated} = \frac{1}{1 + e^{-(score_{true} + \sigma)}}$$

with the $score_{true}$ given by $\ln\left(\frac{1 - PD_{true}}{PD_{true}}\right)$.

- 3 Based on customer elasticity (α) and the magnitude of the spread deviation (m), the probability of leaving can be defined as:

$$P(\text{Leave}) = 1 - e^{-\alpha \cdot m}$$

This probability models the impact of adverse selection.

- 4 For customers who remain with the bank after being offered the spread, the individual loan return r_i is defined as:

$$1 + r_i = \begin{cases} 1 + r + s & : \text{default} = 1 \\ (1 + r + s) \cdot (1 - LGD) & : \text{default} = 0 \end{cases}$$

- 5 Finally, given the individual customer returns, the portfolio return is calculated as:

$$r_{\text{portfolio}} = \frac{1}{N} \sum_{i=1}^N r_i$$

where N is the number of customers who stayed with the bank.

Simulation Setup

The following points outline the simulation setup:

- 1 Define $n = 10,000$ as the total number of customers.
- 2 For each customer, simulate the PD using a random beta distribution with parameters $\text{shape1} = 0.7$ and $\text{shape2} = 37.6$.
- 3 For each customer, simulate a default indicator equal to 1 if a random number from the uniform distribution ($\text{min} = 0$, $\text{max} = 1$) is less than the PD; otherwise, set it to 0.
- 4 Define measurement errors σ as $[2, 0.5, 0.1, 0.01]$ for rating systems with low, medium, high, and perfect accuracy, respectively.
- 5 Assume a constant LGD value of 45% for all customers.
- 6 Assume medium customer elasticity α equals 500.
- 7 Define the interest rate r for all “general” costs as 0.03.
- 8 Calculate the change (increase) in portfolio returns from transitioning from a rating system with low accuracy to systems with medium, high, and perfect accuracy.

Note:

The above simulation setup is merely designed for simulation purposes. Practitioners are encouraged to test real-world figures and adjust the simulation design to incorporate the effects of other parameters as needed.

Simulation Results

Expected Portfolio Returns

##	Accuracy	Expected Return
##	Low	0.0253
##	Medium	0.0284
##	High	0.0298
##	Perfect	0.0300

Portfolio Returns Increase (in bps.)

##	Improvement	Return Increase
##	Low -> Medium	31.05
##	Low -> High	44.85
##	Low -> Perfect	46.70

Distribution of Simulated Portfolio Returns

Low Accuracy Rating System Medium Accuracy Rating System

