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 Competitivity (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 alpha.

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 $\mathtt{r}$ 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 $\mathtt{s}$.
3. The credit spread depends on the Probability of Default (PD) and the Loss Given Default (LGD) of the individual exposures. The bank receives $1 + \mathrm{r} + \mathrm{s}$ if no default occurs. If a default occurs, the bank receives $(1 + \mathrm{r} + \mathrm{s}) \cdot (1 - \mathrm{LGD})$.
4. The expected payoff of the loan must equal the risk-free payoff, leading to the equation:

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

.

5. Solving for the credit spread $\mathtt{s}$ gives:

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

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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:

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

2. Assuming $\mathrm{PD}_{\mathrm{estimated}}$ 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 $ln(\frac{1-PD_{true}}{PD_{true}})$.

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

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

   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:

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

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

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

   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 `shape1 = 0.7` and `shape2 = 37.6`.
3. For each customer, simulate a default indicator equal to 1 if a random number from the uniform distribution (`min = 0`, `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
```