Multifactors Risk Research of China Stock Listed Banks

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Outline

Problem Description

Weighted Average Cost of Capital (WACC)

Critical financial indicator for assessing a company's capital cost:

$$\mathbf{r}_{wacc} = \frac{E}{E+D} \times \mathbf{r}_e + \frac{D}{E+D} \times \mathbf{r}_d \times (1-t)$$

Where:

- E: Market value of equity
- D: Market value of debt
- $\mathbf{r}_e$: Cost rate of equity
- $\mathbf{r}_d$: Cost rate of debt
- t: Corporate tax rate

Risk Premium Component

$$\mathbf{r}^*_{wacc} = \mathbf{r}_{wacc} - \mathbf{r}_f$$

Where $\mathbf{r}_f$ is the risk-free interest rate (SHIBOR)

Research Goal

Primary Objective

Explore causal relationships between financial factors and risk premiums in China's banking sector

Risk Premium Decomposition

- Common (market-driven)
- Idiosyncratic (bank-specific)

Risk Types Analysis

- Default Risk
- Liquidity Risk
- Market Risk

Expected Contribution

Provide insights into fundamental risk structures of China's banking industry

China's Banking Context

Unique Characteristics

- Mixed ownership structures
- Ongoing financial reforms
- Varying government influence
- Evolving regulations

Research Significance

- Different from Western banks
- Requires specialized analysis
- Critical for financial stability
- Informs regulatory policy

Dataset Overview

Data Scope

- 42 listed Chinese banks
- 978 trading days (2019-2022)
- JoinQuant API data source
- Captures pre/post-pandemic conditions

Data Components

Financial Indicators

421 factors including:

- Technical factors
- Fundamentals
- Macroeconomics
- Money flows
- Securities margins
- Industry metrics
- Index data

Bank Information

- Listing details
- Enterprise values
- Market capitalization
- Return rates

Model Parameters

- WACC components
- Risk-free rates
- Market returns
- FCF model inputs

Data Characteristics

Data Preparation

- **Standardized**: All factors normalized
- **Tail-shrinked**: Outliers processed using $[\text{median} - 5\,\text{IQR}, \text{median} + 5\,\text{IQR}]$
- **Industry-neutralized**: Residualized from industry effects
- **Market cap-neutralized**: Adjusted for size effects

Missing Values Processing

- Distinguished between pre-listing/post-delisting missing values and disclosure-related missing values
- Used IterativeImputer with XGBoost for sophisticated imputation

Enterprise Value Weighting

Sectoral Factors Methodology

- Created weighted sectoral factors by enterprise value
- Formula:

$$\text{BankIndustryIndicator}_{j,t} := \frac{\mathbf{v}_{j,t}^{T} \cdot \textbf{Indicator}_{j,t}}{\sum_{i=1}^{42} v_{i,j,t}}$$

- Where:
  - i: Bank index ($i \in \{1, 2, ..., 42\}$)
  - j: Indicator index ($j \in \{1, 2, ..., 421\}$)
  - t: Trading day
  - v: Enterprise value

Methodological Framework

Key Components

- Double Machine Learning framework for causal inference
- Controls for confounding effects across 421 financial indicators
- Combines multiple advanced techniques:
  - K-Shape clustering for risk classification
  - AdaBoost regression with recursive feature elimination
  - Causal Forest models for treatment effect heterogeneity

Risk Classification System

Domain Knowledge Classification

Initial categorization based on banking finance theory:

- Default Risk
- Liquidity Risk
- Market Risk

K-Shape Clustering

- Time-series clustering based on shape similarity
- Updates knowledge-based classifications
- Adapts to observed patterns in factors
- Reveals hidden relationships

K-Shape Risk Reclassification

K-Shape Algorithm Mathematical Formulation

For time series factors $\mathbf{x}$ and $\mathbf{y}$ of length m:

- Cross-correlation at shift q:

$$CC_q(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^{m-q} x_i \cdot y_{i+q}$$

- Shape-based distance (SBD):

$$SBD(\mathbf{x}, \mathbf{y}) = 1 - \max_q \frac{CC_q(\mathbf{x}, \mathbf{y})}{\sqrt{CC_0(\mathbf{x}, \mathbf{x}) \cdot CC_0(\mathbf{y}, \mathbf{y})}}$$

- Clustering $\mathcal{C}^*$ objective: Minimize within-cluster SBD sum

$$\min_{\mathcal{C}} \sum_{k=1}^{K} \sum_{\mathbf{x} \in \mathcal{C}_k} SBD(\mathbf{x}, \mu_k)$$

where μ_k is the shape-based centroid of cluster $\mathcal{C}_k$.

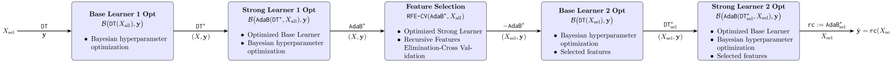
Machine Learning Architecture

CustomRegressor $rc(\cdot)$: Multi-stage Ensemble

1. **Base Learner 1**: Decision Tree with Bayesian hyperparameter optimization and all features
2. **Strong Learner 1**: AdaBoost with optimized Base Learner, all features and Bayesian hyperparameter optimization
3. **Feature Selection**: Recursive Feature Elimination with Cross-Validation and Strong Learner
4. **Base Learner 2**: Decision Tree with Bayesian hyperparameter optimization and selected features
5. **Strong Learner 2**: AdaBoost with optimized Base Learner and Bayesian hyperparameter optimization and selected features

Machine Learning Architecture

$\texttt{rc}(\cdot)$ Architecture:



Risk Premium Decomposition

Mathematical Decomposition Framework

Across bank sector at all trading days (2019-2022), we decompose the WACC risk premium:

$$\mathbf{r}^*_{wacc} = \mathbf{r}_{wacc} - \mathbf{r}_f \quad \text{(Total risk premium)}$$

Prediction-based decomposition:

$$\begin{aligned} \mathbf{r}^*_{common} &= \mathrm{rc}_{r^*}(\mathbf{r}^*_{wacc}) \quad \text{(Prediction from WACC)} \\ \mathbf{r}^*_{idio} &= \mathbf{r}^*_{wacc} - \mathbf{r}^*_{common} \quad \text{(Residual component)} \end{aligned}$$

Treatment risk decomposition using K-Shape clusters:

$$\mathbf{r}^*_{\mathrm{XR}} = \mathrm{rc}_{r^*}(X_{\mathrm{XR}}) \quad \text{(Prediction from WACC)}$$

where $X_{\mathrm{XR}} = [x_i : i \in \mathcal{C}_{\mathrm{XR}}]$ (Liquidity risk factors) and $\mathrm{XR} \in \{\mathrm{DR}, \mathrm{LR}, \mathrm{MR}\}$

- Common risk represents the predictable component based on WACC
- Idiosyncratic risk represents unexplained variations
- Treatment risks are constructed from factors classified by K-Shape clustering

Causal Inference Framework

Double Machine Learning Mathematical Framework

$$Y = \theta(Z)T + g(X) + \varepsilon_Y, \varepsilon_Y \sim \mathcal{N}(0, \sigma^2)$$
$$T = m(X) + \varepsilon_T, \varepsilon_T \sim \mathcal{N}'(0, \sigma'^2)$$

Orthogonalization process:

$$\tilde{Y} = Y - \overbrace{\mathbb{E}[Y|X]}^{\theta(Z)m(X)+g(X)} = \theta(Z)\epsilon_T + \epsilon_Y \quad \text{(Residualized outcome)}$$

$$\tilde{T} = T - \overbrace{\mathbb{E}[T|X]}^{m(X)} = \epsilon_T \quad \text{(Residualized treatment)}$$

$$\text{ATE} := \mathbb{E}[\text{CATE}(Z)] = \mathbb{E}[Y(1) - Y(0)] = \frac{\mathbb{E}[\tilde{Y}\tilde{T}]}{\mathbb{E}[\tilde{T}^2]} = \theta^* \quad \text{(Average Treatment Effect)}$$

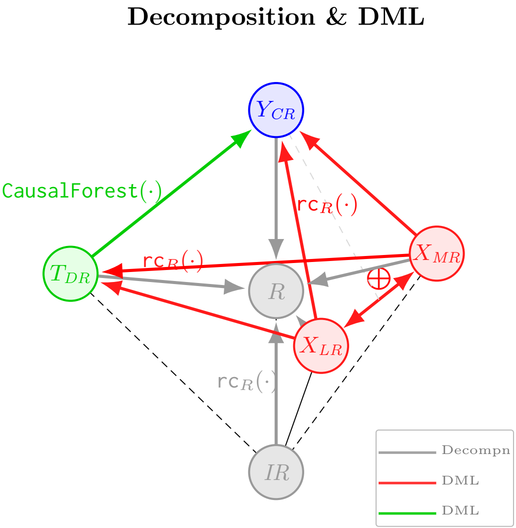
For heterogeneous effects, we estimate:

$$\text{CATE}(Z) := \tau(1, 0, Z) = \mathbb{E}[Y(1) - Y(0)|Z] = \frac{\mathbb{E}[\tilde{Y}\tilde{T}|Z]}{\mathbb{E}[\tilde{T}^2|Z]} = \theta(Z)\text{(Conditional Treatment Effect}$$

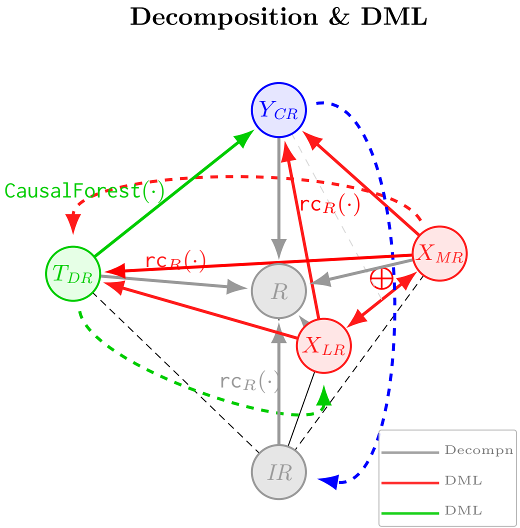
where:

- $\tau(t, t', z) := \mathbb{E}[Y(t) - Y(t')|Z = z] = \mathbb{E}[Y|Z = z, T = t] - \mathbb{E}[Y|Z = z, T = t'] = \theta(Z)(t - t')$: Treatment effect.
- We apply $\hat{\mathbb{E}}[Y|X] = \mathrm{rc}_Y$, $\hat{\mathbb{E}}[T|X] = \mathrm{rc}_T$ and CATE $=$ `CausalForest` here.
- Outcome $Y \in \{Y_{\mathrm{CR}}, Y_{\mathrm{IR}}\}$: Common Risk or Idiosyncrasy Risk.
- Treatment $T \in \{T_{\mathrm{DR}}, T_{\mathrm{LR}}, T_{\mathrm{MR}}\}$: Default Risk or Liquidity Risk or Market Risk, influencing Y.
- Confounder $X \in \{X_{\mathrm{LR}} \oplus X_{\mathrm{MR}}, X_{\mathrm{DR}} \oplus X_{\mathrm{MR}}, X_{\mathrm{DR}} \oplus X_{\mathrm{LR}}\}$: Liquidity Risk & Market Risk or Default Risk & Market Risk or Default Risk & Liquidity Risk, influencing Y and X.
- Feature $Z \in \{T\}$: Feature of entity, not influencing T and X. Chosen as sector trading days: Day and month masks: isMonth.

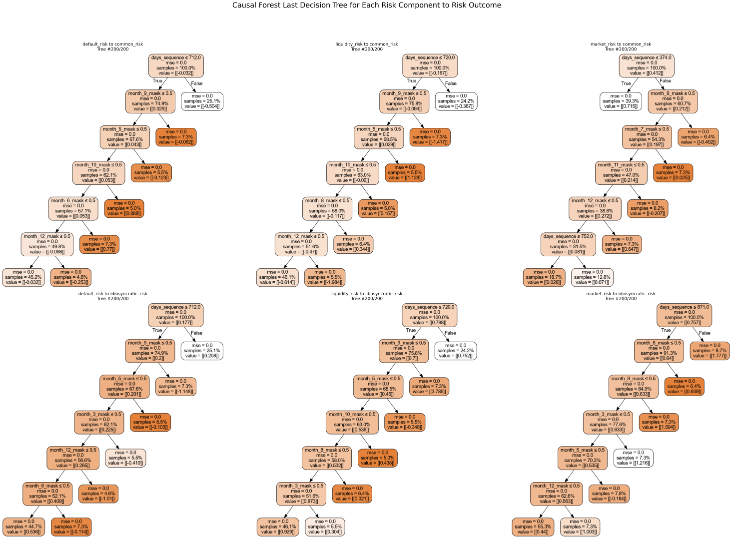
Visual Pipline of Decomp & DML



Visual Pipline of Decomp & DML Iteration



CATE Trees in Causal Forest



CATE Patterns Overview

Directional Effects

- Most relationships: positive CATEs
- Market risk → Common risk: strongest positive effects
- Default risk: moderate positive
- Liquidity risk: variable effects

Magnitude & Stability

- Effect range: -0.1 to +0.3
- Mostly clustered: 0.05-0.15
- Market risk: high stability
- Liquidity risk: high variability

Temporal Heterogeneity

Effect Evolution Over Time

- Stronger effects in earlier periods
- Gradual decay over sample timeframe
- Clear structural breakpoints
- Evolving risk transmission mechanisms

Key Temporal Anomalies

- Market risk: maintains consistent effect strength
- Liquidity risk $\rightarrow$ idiosyncratic risk: sign inversions
- Default risk $\rightarrow$ idiosyncratic risk: complex dependencies

Seasonal Heterogeneity

Reporting Cycle Effects

- Quarter-end months show significant effects
- Financial reporting influences risk relationships
- Regulatory disclosure timing matters

Annual Pattern Breakpoints

- January-February: year-start effects
- July-August: mid-year transitions
- Season-specific risk behavior

Risk-Specific Seasonal Patterns

- Market risk: strong summer effects
- Default risk: amplified year-end effects
- Liquidity risk: negative mid-year, positive year-end

Integrated Temporal-Seasonal Effects

- Risk relationships show increasing seasonal dependency over time
- Banking sector risk transmission increasingly synchronized with:
  - Regulatory cycles
  - Reporting periods
  - Fiscal quarters
- Pattern suggests evolving market maturity and institutional adaptation

Key Findings

Risk Relationship Insights

- Complex causal networks between financial factors and risk premiums
- Different risk types have varying impacts on common vs. idiosyncratic components
- Market risk shows strongest and most stable effects across conditions
- Significant temporal and seasonal patterns in risk transmission

Implications

- **For Regulators**: Consider timing of policy implementation
- **For Investors**: Account for seasonal risk patterns in portfolios
- **For Bank Management**: Adjust risk frameworks for heterogeneous effects

Limitations & Future Research

Limitations

- Period-specific findings (2019-2022)
- Sample limited to listed banks
- Potential unobserved confounders
- Modeling assumptions

Future Research

- Extend to non-listed banks
- Compare with international markets
- Incorporate policy event studies
- Develop predictive risk models

Acknowledgements

- JoinQuant platform for comprehensive financial data
- Open-source Python libraries:
  - pandas, numpy (data processing)
  - scikit-learn (machine learning)
  - xgboost (gradient boosting)
  - econml (causal inference)
  - matplotlib, seaborn (visualization)
  - graphviz (decision tree visualization)
  - scikit-optimize (Bayesian optimization)
  - tslearn (time series clustering)
  - tqdm (progress tracking)

Thank You!

Questions?

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