

The background of the slide features a large, semi-transparent watermark of the Rutgers University Newark seal. The seal is circular and contains the text "RUTGERS UNIVERSITY" around the perimeter and "NEWARK" at the bottom. The central part of the seal is a sunburst design.

Redoing ratio analysis with clustering techniques

Kexing Ding

Xuan Peng

Miklos Vasarhelyi

Yunsen Wang

Peer selection with clustering

- We apply a machine learning technique (clustering) on financial ratios to identify peer firm.
 - SIC/ NAICS codes are commonly used to identify peers
 - Obsolete
 - Infrequent update
 - Focus on production process
 - Ratio selection: choose the set of financial ratios based on research objective
 - For example, if the purpose of the research is to predict a specific corporate event, the selected financial ratios should be related to this event.
 - We do two tests: (1) detecting material accounting misstatements and (2) predicting corporate bankruptcies

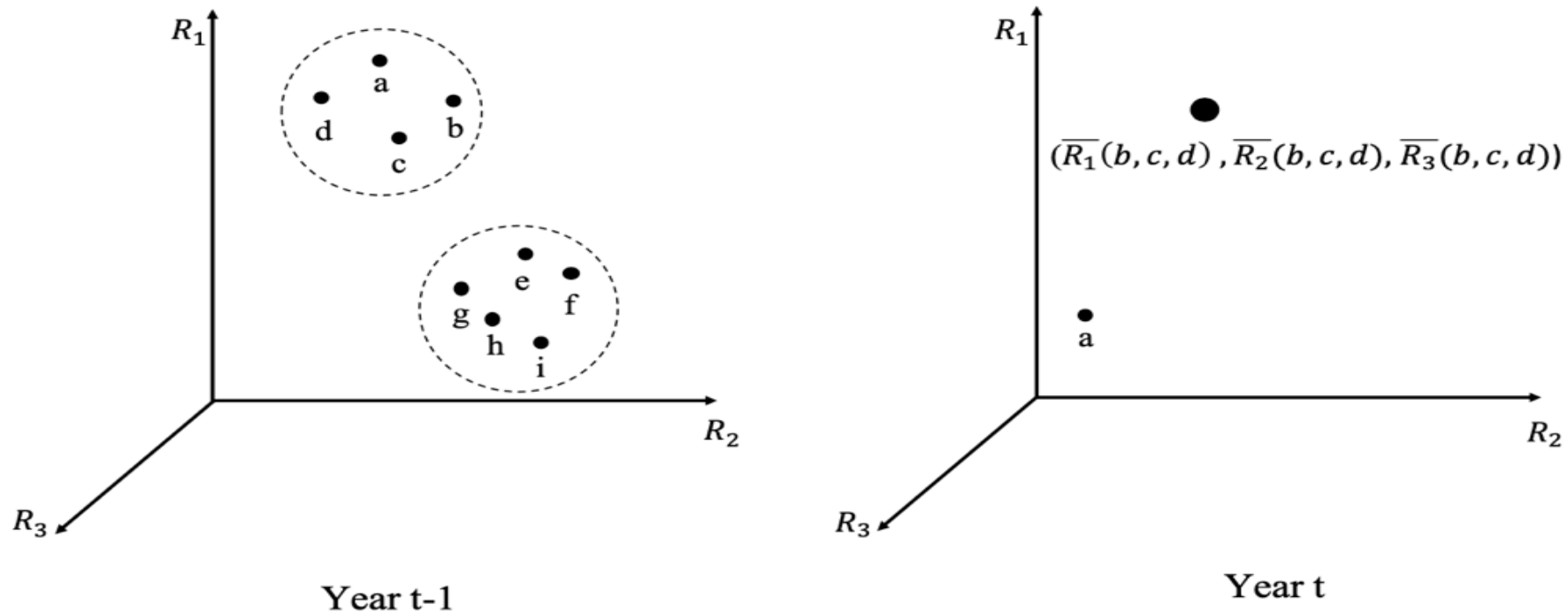
1. Detecting material accounting misstatements

- Ratios in clustering analysis: 8 ratios that are associated with accounting misstatements
 - Sales in receivables ($\text{Receivables}/\text{Sales}$),
 - Gross Margin ($\text{Sales}-\text{Costs of Goods Sold}/\text{Sales}$),
 - Asset Quality ($1 - (\text{Current Assets} + \text{PPE})/\text{Total Assets}$),
 - Sales Growth ($\text{Sales}_t/\text{Sales}_{t-1}$),
 - Depreciation Rate ($\text{Depreciation}/\text{NetPPE}$),
 - SGA Rate ($\text{Sales, general, and administrative expenses}/\text{Sales}$),
 - Leverage ($\text{Total Debt}/\text{Total Assets}$),
 - Accruals ($\text{Total Accruals}/\text{Total Assets}$).

1. Detecting material accounting misstatements

– Clustering

- The clustering algorithm groups firms that are similar to each other in year $t - 1$.
- If in year t , a firm reports differently from the average of its peers, we “redflag” it, and construct a variable, DevScore, to capture its difference from its peers in year t .



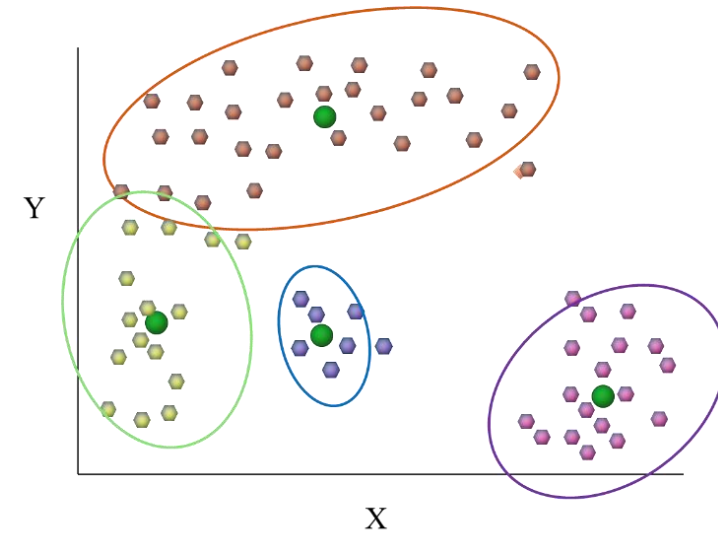
1. Detecting material accounting misstatements

- Out-of-sample test results
- The proportion of actual misstatements in decile groups that are ranked by the estimated misstatement probability by each model.
- Results suggest that the model with clustering DevScore can detect misstatements most efficiently: 40.70% misstating firms in 10th decile; around 85% of misstating firms in the top 5 deciles

Decile	Dechow model (DM)	Dechow model with clustering DevScore	Dechow model with SIC DevScore	Dechow model with NAICS DevScore
1-5	17.44%	15.12%	19.76%	20.94%
6	10.47%	4.65%	6.98%	4.65%
7	11.63%	9.30%	10.47%	12.79%
8	12.79%	12.79%	11.63%	13.95%
9	20.93%	17.44%	25.58%	20.93%
10	26.74%	40.70%	25.58%	26.74%
Total	86 misstatements			

2. Predicting bankruptcy

- Ratios in clustering analysis: 5 ratios that are associated with corporate bankruptcy
 - Net working capital to total assets ratio (WC/TA)
 - Retained earnings to total assets ratio (RE/TA)
 - Earnings before interest and taxes to total assets ratio (EBIT/TA)
 - Market value of equity to book value of total liabilities (ME/BL)
 - Sales to total assets (SALE/TA)
- Clustering: peers with similar “bankruptcy” ratios
- Compute *DevScore* to capture a firm’s differences from its peers



1. Predicting bankruptcy

– Out-of-sample test results

- The proportion of actual bankruptcies in decile groups that are ranked by the estimated bankruptcy probability by each model.
- Results suggest that the Shumway model with clustering DevScore outperforms other models in bankruptcy predicting: 88% of bankruptcy firms in the top decile, higher than other three models.

Decile	Shumway model	Shumway model with clustering DevScore	Shumway model with SIC DevScore	Shumway model with NAICS DevScore
1-5	2.89%	0.97%	1.93%	1.93%
6	0.96%	0.00%	0.96%	2.88%
7	0.00%	0.96%	2.88%	0.96%
8	2.88%	1.92%	2.88%	1.92%
9	11.54%	7.69%	10.58%	12.50%
10	81.73%	88.46%	80.77%	79.81%
Total	104 bankruptcies			

Thank you!