Evaluating Stability of Financial Systems: CAMEL-DEA and Pareto Approaches

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Abstract

The present investigation delves into stability evaluation indicators for banking and insurance institutions. A CAMEL-DEA model was employed to devise stability and efficiency evaluation indicators for twelve major banks within China, stretching from 2007 to 2023, while also analyzing the Pareto performance within the insurance sector. The findings indicate that systemic upheavals, inclusive of the 2008 financial downturn and the COVID-19 global crisis, have exercised significant impact upon banking performance. State-owned financial institutions have demonstrated superior resilience in comparison to joint-stock banks, a result attributable to robust capital reserves, governmental backing, and an extensive customer base. Simultaneously, the Pareto performance within the insurance industry has generally been satisfactory, serving as a respectable reflection of organizational stability.

Introduction

The 2007–2009 Great Recession underscored the need to study financial stability, though its definition remains somewhat ambiguous (Affandi *et al*., 2021). **Stability** can be seen as the system's ability to recover from shocks or resist disturbances. This paper explores suitable stability indicators for **banks** and **insurance companies**, considering both internal and external factors. For **12 major Chinese banks**, DEA techniques are used to create an efficient CAMEL index from 2007 to 2023, evaluating capital adequacy and asset quality (Boubaker *et al*., 2024). External shocks are quantified using the Pareto distribution to assess the bankruptcy probability of **5 life insurance companies** post-COVID-19, comparing this with internal indicators (comprehensive solvency adequacy ratio) to validate the model's effectiveness, offering stability references for the financial sector.

Methodology

- **Bank:**

The Data Envelopment Analysis (DEA) model assesses production efficiency by identifying decision-making units (DMUs) that maximize output with minimal input but struggles with surplus inputs or deficient outputs. The DEA-SBM (Slacks-Based Measure) model enhances efficiency evaluation by optimizing individual inputs or outputs to minimize surpluses and deficiencies.

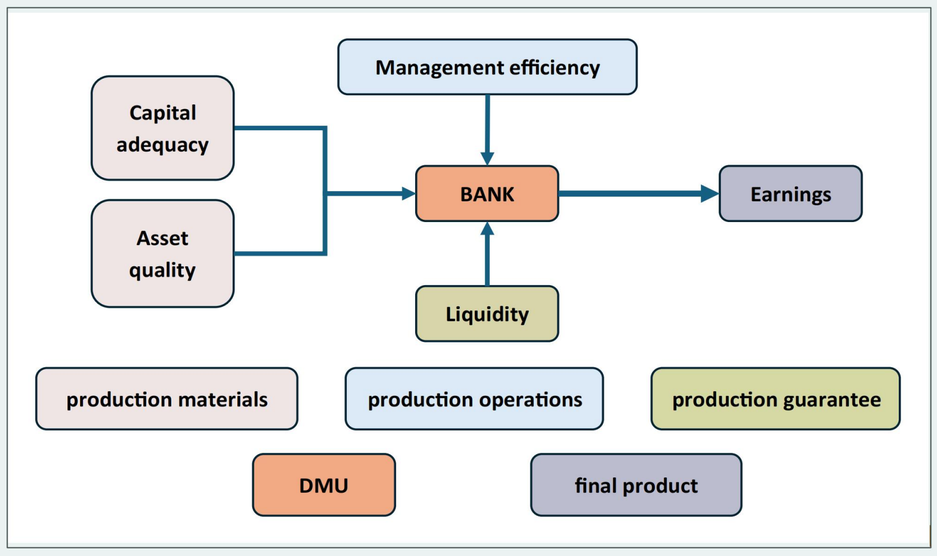

Figure 1

In banking, combining the **DEA-SBM** model with the **CAMEL** rating system—using Capital Adequacy (C), Asset Quality (A), Management Quality (M), and Liquidity (L) as **inputs**, and Earnings (E) as **output**—provides a robust framework for assessing bank efficiency and stability, useful for regulatory and strategic purposes.

- **Insurance company:**

Pareto distribution is a power distribution found from a large number of real-world phenomena, which is widely used to quantify the number of disasters caused by various factors.

$$p(x) = \begin{cases} 0, & \text{if } x < x_{\min}; \\ \frac{k\, x_{\min}^{k}}{x^{k+1}}, & \text{if } x > x_{\min}. \end{cases}$$

Current research on the bankruptcy theory of insurance companies suggests that bankruptcy occurs when losses exceed the initial surplus and ongoing income. This study focuses on the numerical implementation of the model and compares the results with stability indicators to test the validity of the Pareto distribution in financial markets.

$$S(t) = \sum_{i=1}^{N(t)} X_i$$

$$U(t) = u + ct - S(t),$$

$$\psi(u) = \Pr(U(t) < 0 \quad \text{for some } t > 0).$$

$$P(\text{Bankruptcy}) = P(S(t) > u + ct) = \int_{u+ct}^{\infty} f(x)\, dx$$

$$P(\text{Bankruptcy}) = \int_{u+ct}^{\infty} \frac{\alpha x_m^{\alpha}}{x^{\alpha+1}}\, dx$$

Figure 2

In this study, we applied statistical tests to evaluate whether the overall insurance company losses follow a Pareto distribution, as shown in Figure 2.

Empirical Results

Bank\Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
BoC	1.05668	0.70480	0.91080	0.91000	0.85544	0.86616	0.89131	0.90788	1.00348	1.01500	1.00196	0.86433	0.81732	0.85504	0.73982	0.67772	0.65856
ICBC	0.84034	0.85003	0.92568	1.01046	0.98323	0.99244	0.97865	0.99382	1.00884	1.02976	1.02580	1.00994	0.95709	0.97777	1.00326	1.00135	0.69168
CCB	0.89667	1.00826	1.03286	1.00072	1.02253	1.01907	1.02218	1.01101	1.00021	0.97116	0.97498	1.00309	1.00654	1.00301	0.94868	0.75455	0.71354
BoCom	1.06668	1.06646	1.06898	1.08486	1.08478	1.06013	1.03889	1.00431	0.90155	1.00443	1.00301	0.80460	0.74088	0.75910	0.72621	0.66675	0.63151
CMB	1.17350	1.09743	0.79431	0.89489	0.97000	1.00550	1.01079	0.96603	0.96511	0.91475	1.00410	1.08385	1.18232	1.17424	1.22603	1.26710	1.43269
SPDB	0.55877	0.78096	0.68564	0.76226	0.79756	0.83944	0.89832	1.03092	0.90721	1.00604	1.00368	0.80977	0.76743	0.72994	0.63373	0.58542	0.48935
CEB	0.51299	0.69139	0.59778	0.76329	0.84043	0.85523	0.82853	0.88765	0.84247	0.78928	0.72640	0.74867	0.71359	0.70556	0.68890	0.64753	0.59216
CMBC	0.62370	0.66056	0.76105	1.00112	1.02796	1.02266	1.00139	1.03345	1.01422	0.83574	0.81447	0.79424	0.75059	0.58671	0.53557	0.52717	0.51732
Huaxia Bank	0.35747	0.32386	0.41332	0.53306	0.61402	0.71725	0.74088	0.78383	0.85910	0.79429	0.76839	0.73289	0.69354	0.68491	0.64809	0.60845	0.62768
CIB	0.83447	0.84442	0.89209	0.87970	0.84212	0.82957	0.85525	0.89552	0.90511	0.81110	0.86330	0.83576	0.79455	0.81184	0.82370	0.79780	0.68414
CITIC	0.86254	0.86228	0.88793	0.91278	0.90147	0.81852	0.88399	0.82514	0.76880	0.69973	0.73411	0.73033	0.68656	0.67070	0.63854	0.64922	0.67069
Nanjing Bank	1.11496	1.35521	1.16602	1.05720	1.06118	1.02793	0.83687	0.84312	0.81431	0.73803	0.78108	0.79004	0.77069	0.77916	0.78903	0.73330	0.69755

Table 1

Table 1 presents the efficiency data of 12 Chinese banks from 2007 to 2023, analyzed using the CAMEL-DEA methodology.

- **Bank:**

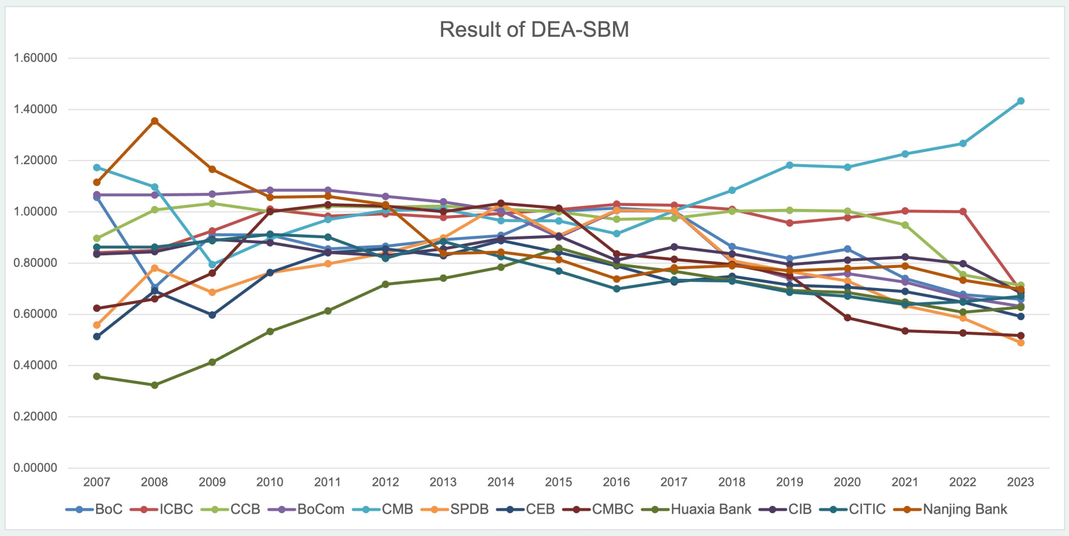

Figure 3

Figure 3 presents a line chart of the data, with trends clearly delineating three distinct periods for analysis.

- 2007-2013: The first phase saw significant **fluctuations** in bank efficiencies, exemplified by CMB declining from 1.173 in 2007 to 0.794 in 2009 due to the global financial crisis.
- 2013-2018: The second phase featured **relative stabilization**, with efficiency levels converging between 0.8 and 1.
- Post-2019: The third phase reveals significant **divergence** in efficiency. Notably, CMB reaching a peak of 1.433 in 2023. This period highlights increasing disparities in bank performance, particularly intensified by the COVID-19 pandemic.

- **Insurance company:**

Figure 4 shows a **negative** correlation between the numerically realized bankruptcy probability and the comprehensive solvency margin ratio of an insurance company. Figure 5 confirms this correlation through further analysis. The **linear fitting** in Figure 6 supports the relationship between these indicators, verifying the model's effectiveness. Among the five companies analyzed, four met the **negative** correlation criteria, while one did not achieve suitable linear fitting results.

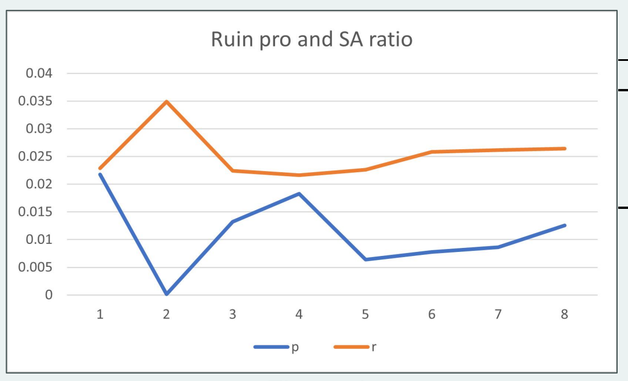

Figure 4

Pairwise correlations

Variables	(1)	(2)
(1) p	1.000	
(2) r	-0.737* (0.037)	1.000

****p<0.01, **p<0.05, *p<0.1*

Figure 5

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. regress p r

      Source |       SS       df       MS              Number of obs =       8
-------------+------------------------------           F(1, 6)       =    7.12
       Model |  .000179253     1  .000179253           Prob > F      =  0.0371
    Residual |  .000151106     6  .000025184           R-squared     =  0.5426
-------------+------------------------------           Adj R-squared =  0.4664
       Total |  .000330359     7  .000047194           Root MSE      =   .00502

------------------------------------------------------------------------------
           p | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
           r |  -.0117662   .0044103    -2.67   0.037    -.0225578   -.0009746
       _cons |   .0409204   .0113206     3.61   0.011     .0132198    .068621
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Figure 6

Conclusion

Economic crises like the 2008 financial crisis and COVID-19 pandemic caused significant fluctuations in bank efficiency, with renewed instability in 2022. China Merchants Bank led in efficiency due to strategic retail expansion, while **state-owned banks** showed **greater stability** due to stronger capital, government support, and extensive customer bases. In the **insurance sector**, variations in **business structures** influenced correlations with stability, where strong correlations indicated stable profits, and weaker ones led to volatility between gains and losses. The study emphasizes the importance of **capital reserves** and **strategic management** in enhancing financial stability, validating the use of the Pareto distribution for quantifying shock losses. However, it notes the need for further research to address complex factors affecting predictive accuracy.

Key References

[1] Boubaker, S., Ngo, T., & Samitas, A. (2024). An MCDA composite index of bank stability using CAMELS ratios and Shannon entropy. *Annals of Operations Research.* https://doi.org/10.1007/s10479-024-06023-3 [2] Chen, W.-D., Chen, Y., & Huang, S.-C. (2021). Liquidity risk and bank performance during financial crises. *Journal of Financial Stability, 56,* 100906. https://doi.org/10.1016/j.jfs.2021.100906 [3] Han, M. (2012) 'The People's Bank of China during the global financial crisis: Policy responses and beyond', Journal of Chinese Economic and Business Studies, 10(4), pp. 361–390. https://doi.org/10.1080/14765284.2012.724982 [4] Phan, D. H. B., Iyke, B. N., Sharma, S. S., & Affandi, Y. (2021). Economic policy uncertainty and financial stability–Is there a relation? *Economic Modelling, 94,* 1018-1029. https://doi.org/10.1016/j.econmod.2020.02.042