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Research article

Empirically benchmarked relative financial structure and bank efficiency: DEA evidence from U.S. depository institutions (2000–2020)

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Abstract: Despite successive Basel reforms, capital adequacy ratios continue to receive disproportionate regulatory emphasis relative to the broader CAMELS supervisory framework—an emphasis repeatedly criticized as insufficient to capture the structural determinants of institutional efficiency. This study introduces and empirically validates the concept of an empirically benchmarked relative financial structure: a multidimensional framework comprised of the holistic configuration of financial ratios that collectively determine the U.S. depository institution performance. Using 7136 institution-year observations from the Federal Deposit Insurance Corporation (FDIC) database, representing 81.2% of the total U.S. depository institution assets over the period January 2000 to September 2020, a sequential two-stage methodology is employed. In the first stage, an Ordinary Least Squares (OLS) regression with backward elimination identifies 28 financial ratios significantly predicting Return on Equity (ROE), Return on Assets (ROA), and Net Interest Margin (NIM), with model fit ranging from 69.4% to 82.2% of the explained variance (28–39% after excluding mechanically related predictors; Section 4.1). In the second stage, an input-oriented Data Envelopment Analysis (DEA) under Variable Returns to Scale (VRS) generates efficiency scores for all institution-year observations. The study yields four principal findings: first, retained earnings, net loans and leases, and total liabilities are the dominant structural determinants of profitability, collectively accounting for 26.9% of the combined contribution share; second, efficient institutions systematically record higher non-interest expenses than inefficient—a descriptive pattern that diverges from, rather than directly tests, the cost-minimization efficiency paradigm, since a non-interest expense is not a DEA input in this profitability-oriented specification—while core capital ratios exhibit a non-monotonic relationship with efficiency; third, the efficiency ordering Large > Small > Medium > Giant is consistent with diseconomies of scale and suggests the primacy of structural composition over size, though a formal scale-efficiency decomposition was not conducted; and fourth, savings banks and savings associations

record persistently lower efficiencies, associated with the mortgage concentration and structural rigidity. An empirically grounded monitoring model with calibrated empirical benchmark margins and limiting thresholds for 28 financial ratios—with benchmark patterns observed consistently across the institutional sizes and charter types examined—is proposed as a practical performance-monitoring tool, with early-warning applications identified as a direction for future validation.

Keywords: bank efficiency; relative financial structure; data envelopment analysis (DEA); financial regulation; U.S. depository institutions; net interest margin; performance monitoring; capital adequacy; OLS regression; FDIC

JEL Codes: G21, G32, G39

Abbreviations: DEA: Data Envelopment Analysis; FDIC: Federal Deposit Insurance Corporation; NIM: Net Interest Margin; OLS: Ordinary Least Squares; ROA: Return on Assets; ROE: Return on Equity; VRS: Variable Returns to Scale

1. Introduction

The 2008–2009 financial crisis exposed fundamental weaknesses in how the banking efficiency is assessed and regulated. Despite successive Basel reforms (BCBS, 2010), capital adequacy ratios and risk-weighted assets continue to receive disproportionate regulatory emphasis within the broader CAMELS-based U.S. supervisory framework—an emphasis repeatedly criticized as insufficient to capture the true determinants of institutional health (Admati and Hellwig, 2013; Haldane, 2012). The persistence of profitability disparities and systemic vulnerabilities across institutional types and sizes underscores a critical limitation: efficiency in banking cannot be reduced to any single metric, yet regulatory practice has largely treated it as such.

Existing studies based on data envelopment analysis (DEA) and stochastic frontier analysis (SFA) have advanced have advanced the understanding of cost and profit efficiency, scale economies, and capital–risk interactions (Berger and Humphrey, 1997; Ding and Sickles, 2018; Coelli et al., 2005). However, a persistent limitation runs through this literature: efficiency is assessed through isolated financial indicators rather than through the integrated configuration of an institution's entire financial structure, producing a fragmented evidence base of limited regulatory utility. No prior study has empirically defined and validated an empirically benchmarked relative financial structure—a comprehensive ratio-based framework encompassing the full balance sheet and income statement—as a unified efficiency predictor for U.S. depository institutions across an extended multi-cycle period.

This study addresses that gap by proposing and empirically testing the relative financial structure framework using 7136 institution-year observations covering January 2000 to September 2020. Four primary research objectives are pursued: (i) identifying financial ratios most significantly affecting profitability and efficiency; (ii) assessing the efficiency variation across time, asset size, and regulatory charter type; (iii) determining whether efficient institutions share a generalizable structural pattern; and (iv) developing a practical monitoring model with empirically derived ratio thresholds for regulatory and managerial application. The study tests four hypotheses: H1—specific financial ratios drawn from the full balance sheet and income statement significantly influence efficiency; H2—efficient institutions

exhibit consistent and distinctive structural patterns; H3—an empirically benchmarked relative financial structure applies across institutions regardless of size or charter type; and H4—capital adequacy alone systematically underestimates the role of the broader financial structure in determining the efficiency.

This research makes three contributions: theoretically introducing the benchmarked relative financial structure concept; empirically providing an extensive DEA-based efficiency assessment of U.S. depository institutions over twenty years encompassing two major financial cycles, complementing recent DEA studies of U.S. banks using alternative ratio frameworks (e.g., Kweh et al., 2024); and practically proposing a structure-based monitoring model with calibrated thresholds for 28 financial ratios applicable to regulators and managers. The remainder of the paper is organized as follows: Section 2 reviews the literature; Section 3 describes the methodology; Section 4 presents the results and discussion; Section 5 presents the conclusions; and Section 6 covers the author's contributions and declarations.

2. Literature review

2.1. Measuring bank efficiency

Efficiency measurement has been dominated by parametric SFA and non-parametric DEA (Berger and Humphrey, 1997; Coelli et al., 2005). Berger et al. (1993) showed that the profit-function efficiency systematically exceeds cost-function estimates, suggesting revenue-side factors are as important as cost control. Their landmark review of 130 studies across 21 countries confirmed a persistent divergence between the cost and the profit efficiency, calling the prevailing regulatory emphasis on cost reduction into question. Seiford and Zhu (1999) introduced important size-related efficiency variations, while Diego and Kumbhakar (2014) demonstrated that profit efficiency estimates are predominantly driven by cost inefficiencies. Simoens and Vander Vennet (2021), thereby comparing U.S. and European banks, identified the net interest margin as the dominant profitability driver—directly informing this study's use of net interest margin (NIM) as a core output variable. Collectively, no consensus exists on the optimal DEA input–output set for depository institutions, and the role of the broader financial structure in shaping efficiency frontiers remains underexplored. Recent DEA applications to U.S. commercial banks using CAMEL-based ratio frameworks (Kweh et al., 2024) and two-stage DEA–regression designs (Joaquim et al., 2024) confirm the continued reliance on partial ratio sets rather than a unified financial-structure framework.

2.2. The capital–risk–efficiency nexus

The moral hazard hypothesis posits that insured, inefficient banks take excessive risks, thereby exploiting deposit insurance safety nets (Eisenbeis and Kwan, 1996; Ding and Sickles, 2018), while the capital buffer theory argues that undercapitalized banks reduce risk to rebuild regulatory buffers (Aggarwal and Jacques, 2001). The empirical evidence is mixed: Hoffman (2010) documented a significant inverse relationship between capital adequacy and profitability; Hussain and Hassan (2012) found competition inversely related to efficiency; and Roshanthi (2021) demonstrated that capital regulation effects substantially vary by institutional type—confirming that no universal capital threshold guarantees an efficient behavior. Ding and Sickles (2018) demonstrated that the frontier efficiency, capital structure, and portfolio risk are jointly determined, underscoring the inadequacy of

treating capital adequacy as an exogenous efficiency determinant. Consistent with this, Saif Ullah et al. (2023) found that governance quality and financial leverage remain significant DEA-efficiency determinants, even after controlling for capital adequacy, in an emerging-market banking context.

2.3. Regulatory frameworks and their limitations

Basel-based frameworks have attracted sustained scholarly criticism. Admati and Hellwig (2013) argued that risk weights are structurally prone to manipulation through securitization and off-balance-sheet instruments. Haldane (2012) empirically demonstrated that simple leverage ratios predicted bank distress during the 2008 crisis more reliably than risk-weighted assets (RWA)-based capital ratios. Acharya et al. (2014) showed that stress tests systematically underestimated actual risk exposures, particularly for institutions with complex trading portfolios. Josef et al. (2025) demonstrated that aggregate RWA modeling underestimates credit risk at the portfolio level, recommending a granular ratio-based analysis—consistent with this study's disaggregated approach. The 2024 legal challenge by major U.S. banks against the Federal Reserve stress testing methodologies (Roy, 2024) further illustrates unresolved tensions between regulatory credibility and model transparency. This finding is reinforced by Behn et al. (2025), who argue that simpler leverage-based constraints outperform model-based risk-weighted capital regulation in transparency and resilience.

2.4. Research gap: toward a structure-based approach

Borio and Drehmann (2009) advocated for dynamic models capturing entire financial structures over the credit cycle. Bushman and Williams (2012) showed that loan loss provisioning interactions significantly shape risk-taking disciplines. DeYoung and Roland (2001) and Rogers (1998) demonstrated that non-interest income and strategic operating costs generate efficiency gains not captured by cost-minimization models. Despite these contributions, no study has systematically defined and empirically validated an empirically benchmarked relative financial structure—a comprehensive ratio-based framework encompassing the full balance sheet and income statement configuration—as a unified efficiency predictor for U.S. depository institutions. This study directly addresses that gap by integrating ordinary least squares (OLS)-based variable selection with DEA efficiency scoring across a twenty-year, multi-cycle dataset.

3. Materials and methods

3.1. Two-stage sequential framework

This study employs a sequential two-stage empirical framework. In the first stage, an OLS regression with backward elimination identifies financial ratios significantly linked to institutional profitability, empirically defining the components of the relative financial structure. In the second stage, input-oriented DEA under variable returns to scale (VRS) uses the most discriminative subset to measure the relative institutional efficiency. This sequential design ensures that DEA variables are empirically grounded (Golany and Roll, 1989; Worthington, 2000), separates variable identification from efficiency measurement, and aligns with the established combined parametric–non-parametric

practice (Abu-Alrop, 2025; Coelli et al., 2005). All regression analyses were conducted using IBM SPSS v27, DEA computations using WIN4DEAP2, and data processing using Microsoft Excel 2019.

3.2. Stage 1: OLS regression and variable construction

Following the financial intermediation approach to bank production (Sealey and Lindley, 1977), 137 absolute financial variables were extracted from qualifying institution annual reports. To ensure cross-institutional comparability and control for size effects, all variables were converted into relative metrics—ratios scaled to total assets, average assets, average equity, or total loans, as appropriate. Three profitability indicators serve as dependent variables: return on equity (ROE) (net income / average total equity), measuring shareholder value generation; return on assets (ROA) (net income / average total assets), capturing overall asset utilization efficiency; and NIM ((total interest income−total interest expense) / average revenue-generating assets), reflecting the core lending profitability (Demirguc-Kunt and Huizinga, 1999). The OLS model is as follows:

$$Y_j = a_j + \sum_{i=1}^{28} B_{ij} X_i + \mathcal{E}_j, \quad (1)$$

where Y_j represents each profitability indicator (ROE, ROA, NIM), α_j is the intercept, β_{ij} are the estimated coefficients for each financial ratio X_i, and $\mathcal{E}_j$ is the error term. Here, j = 1, 2, 3 indexes the three dependent profitability models (ROE, ROA, NIM, respectively), and i = 1, …, 28 indexes the pool of financial ratios retained across the three backward-elimination procedures; because elimination was separately run for each model, not every ratio is retained in every model, as reflected by the "—" entries in Table 3. A backward elimination procedure was iteratively applied, thereby removing variables that failed to achieve statistical significance at the $p < 0.05$ threshold across any of the three profitability models. This process reduced the initial pool of 137 variables to 28 financial ratios collectively defining the relative financial structure. Reported t-statistics reflect the pooled-sample association strength rather than the panel-robust inference; the unbalanced nature of the panel (institutions enter and exit the $2 billion asset threshold over the sample period) and the software used for estimation did not permit fixed-effects or clustered-standard-error specifications in this study. Table 1 presents descriptive statistics for all variables. Note that roe, roa, and nim are reported in Table 1 for descriptive purposes alongside the explanatory ratios, but they exclusively serve as the dependent variables Y_j in Equation (1) and are not among the 28 explanatory ratios X_i used to predict them.

Table 1. Descriptive statistics of financial variables (N = 7136).

Variable	Mean	Standard Deviation	Median	Minimum	Maximum	Percentile 25	Percentile 75	Skewness
roe	9.30%	13.20%	9.59%	−352.67%	95.19%	5.92%	13.94%	−5.47
roa	1.00%	1.33%	1.02%	−17.01%	17.50%	0.66%	1.36%	−0.85
nim	3.76%	1.94%	3.57%	−2.61%	27.67%	3.04%	4.08%	5.34
nii	1.54%	2.58%	0.93%	−8.30%	39.70%	0.53%	1.55%	5.72
cofrga	1.53%	1.32%	1.07%	0.00%	10.22%	0.48%	2.32%	1.14
nie	2.95%	2.10%	2.60%	−1.31%	28.71%	2.05%	3.22%	4.48
reea	3.30%	11.45%	3.37%	−352.67%	80.55%	0.25%	7.36%	−7.84
ncho	0.84%	1.38%	0.38%	−12.56%	24.75%	0.13%	1.04%	4.56
lev	30.03%	29.74%	12.22%	0.01%	94.11%	9.38%	62.11%	0.97
pfllal	29.54%	41.54%	1.56%	0.01%	99.80%	1.05%	87.49%	0.81
nlal	46.37%	32.28%	60.47%	0.00%	99.24%	3.11%	72.86%	−0.45
lcc	9.61%	3.80%	8.99%	−1.96%	85.21%	7.70%	10.42%	5.50
oass	3.78%	2.79%	3.35%	0.08%	53.55%	2.36%	4.44%	5.87
tlia	88.92%	4.28%	89.73%	14.69%	100.18%	87.41%	91.42%	−3.61
ibde	59.86%	14.43%	60.58%	0.00%	94.05%	53.55%	68.25%	−1.11
obre	8.82%	11.20%	5.60%	0.00%	91.14%	1.36%	11.83%	2.94
olia	1.57%	2.00%	1.04%	0.04%	62.19%	0.67%	1.72%	9.54
nclal	1.11%	1.88%	0.55%	0.00%	27.81%	0.27%	1.15%	5.15
uclin	0.39%	0.24%	0.35%	0.00%	4.82%	0.27%	0.45%	7.18
gaoi	1.98%	2.62%	1.02%	0.00%	25.79%	0.17%	2.86%	2.68
lsbfrs	19.23%	16.22%	15.73%	0.00%	100.83%	8.25%	24.94%	1.60
adf3mol	0.27%	1.06%	0.03%	0.00%	27.62%	0.00%	0.14%	10.85
lsred3mol	0.19%	1.01%	0.01%	0.00%	27.60%	0.00%	0.06%	12.31
ainas	0.85%	1.49%	0.42%	0.00%	24.32%	0.20%	0.86%	5.43
lsreuns	0.67%	1.38%	0.26%	0.00%	24.31%	0.10%	0.61%	5.80
lsfreuns	0.25%	0.65%	0.09%	0.00%	13.10%	0.03%	0.23%	9.02
lsnnpuns	0.19%	0.43%	0.06%	0.00%	11.36%	0.01%	0.19%	8.81
dsec	19.46%	13.97%	16.80%	0.00%	98.58%	10.38%	25.16%	1.50
cdocs	6.48%	33.02%	3.57%	0.00%	2076.95%	0.00%	7.97%	48.46
tsde	64.93%	16.22%	68.80%	0.00%	93.74%	58.92%	75.47%	−1.65
code	61.15%	19.46%	65.91%	0.00%	94.05%	53.10%	74.63%	−1.27

Note: All values expressed as percentages. The extreme minimum values shared by roe and reea (−352.67%) correspond to the same institution−year observation, consistent with their shared accounting relationship discussed in Section 4.1. Abbreviations: adf3mol: Assets delinquent for 3 months or longer, ainas: Assets in nonaccrual status, cdocs: Cash dividends on common stock, code: Core deposits, cofrga: Cost of funding revenue−generating assets, dsec: Debt securities, gaoi: Goodwill and other intangibles, ibde: Interest−bearing deposits, lcc: Leverage (core capital) ratio, lev: Leverage, lsbfrs: Loans secured by family real estate, lsfreuns: Loans secured by family real estate under the nonaccrual status, lsnnpuns: Loans secured by nonfarm nonresidential properties under the nonaccrual status, lsred3mol: Loans secured by real estate delinquent for 3 months or longer, lsreuns: Loans secured by real estate under the nonaccrual status, ncho: Net charge−offs, nclal: Noncurrent loans and leases, nie: Noninterest expense, nii: Noninterest income, nim: Net interest margin, nlal: Net

loans and leases, oass: Other assets, obre: Other borrowed resources, olia: Other liabilities, pfllal: Provisions for loan and lease losses, reea: Retained earnings, roa: Return on assets, roe: Return on equity, tlia: Total liabilities, tsde: Time and savings deposits, uclin: Uncollected loans income. Source: Compiled by the author from FDIC database.

3.3. Stage 2: Data envelopment analysis (DEA)

DEA is a non−parametric linear programming technique that measures the relative efficiency by constructing piecewise−linear production frontiers from observed input–output combinations (Charnes et al., 1978; Farrell, 1957; Cook and Zhu, 2008). An input−oriented VRS model is adopted, specifically the Banker-Charnes-Cooper (BCC) formulation of Banker et al. (1984), which extends the original Charnes, Cooper, and Rhodes (CCR) model (Charnes et al., 1978) by relaxing the constant−returns−to−scale assumption through the convexity constraint $\Sigma\lambda_j = 1$ in Equation (2): input−oriented because bank managers exercise greater discretionary control over input allocation—including funding costs, capital deployment, and operational expenditure—than over output volumes, which are subject to market demand and competitive conditions (Huguenin, 2012; Coelli et al., 2005); and VRS because U.S. depository institutions span assets from $2 billion to over $2 trillion, making the CRS assumption of uniform scale efficiency empirically untenable. As all six DEA variables in Table 2 are ratios, the BCC (VRS) formulation—rather than CCR (CRS)—is methodologically required for a further reason: CRS's proportional−scalability property is violated by the ratio data (Hollingsworth and Smith, 2003). The same institutional scale heterogeneity motivating VRS also partially mitigates the residual ratio−convexity concerns, since VRS imposes no single proportional benchmark across institutions; nonetheless, dedicated ratio−DEA technologies (Olesen et al., 2015) could examine this further in future work.

The input−oriented VRS DEA model minimizes θ_k subject to the following:

$$y_{rk} - \sum_j \lambda_j y_{rj} \leq 0, \quad \theta_k x_{ik} - \sum_j \lambda_j x_{ij} \geq 0, \tag{2}$$

where θ_k is the efficiency score of the institution k ($\theta_k = 1$ indicates full efficiency), λ_j are peer weights defining the reference frontier, y_{rj} and x_{ij} denote the outputs and inputs, respectively, and the convexity constraint $\Sigma\lambda_j = 1$ enforces the VRS assumption. The subscript k denotes the institution−year observation (DMU) currently being evaluated, while j indexes all institution−year observations in the sample, including k itself, that may serve as peers on the efficiency frontier; $r = 1, 2$ denotes the two outputs (ROE, NIM), and $i = 1, \ldots, 4$ denotes the four inputs (retained earnings ratio, provisions ratio, core capital ratio, and cash dividends ratio) listed in Table 2. An institution is only fully efficient when $\theta_k = 1$ and all slacks equal zero. Although 7136 observations far exceed the minimum DMU count implied by Dyson et al.'s (2001) rule even for all 28 ratios, the discriminating power also depends on the number and correlation structure of the input/output dimensions themselves, not sample size alone; too many correlated ratios inflate the share of institutions classified as fully efficient regardless of N. To preserve the discriminative power of DEA, a stepwise elimination procedure was applied to the 28 OLS−identified ratios—using the Wilcoxon Signed Rank test and the same guideline that the DMU count exceed twice the combined input–output count. The stepwise reduction proceeded iteratively: at each step, the mean DEA efficiency score across all institution−year observations was computed both with and without the candidate variable, and a paired Wilcoxon signed−rank test compared the two efficiency distributions. If removing the variable changed the mean efficiency score by more than 20%, then the variable was retained as discriminating; otherwise, it was excluded. The variable contributing the smallest change was dropped at each iteration, and the procedure was repeated until no further

removable variable remained, yielding six final variables (Table 2). All data were adjusted to strictly positive values by replacing zeros and negatives with 0.0001 to satisfy the linear programming constraints (Cooper et al., 2007). The number and percentage of institution−year observations with a zero or negative value for each DEA variable were as follows: roe (535, 7.50%), nim (14, 0.20%), reea (1,248, 17.49%), pfllal (3, 0.04%), lcc (1, 0.01%), and cdocs (1,985, 27.82%). The elevated share for cdocs predominantly reflects institutions that simply did not distribute a common−stock dividend in a given year—a routine and economically meaningful zero rather than a data irregularity—whereas the non−positive values in roe and reea are mainly concentrated during the 2008–2010 crisis period and reflect genuine reported losses. These observations were retained via constant substitution rather than excluded to avoid removing distressed institution−years central to the crisis−period analysis in Section 4.3 and introducing survivorship bias. Alternative treatments (e.g., translation−invariant additive models, range−directional measures, or the nonpositive−data−robust DEA model of Yeh (2025)) exist in the DEA literature and carry their own interpretability trade−offs; comparing them may be considered in future work.

Table 2. DEA input and output variables.

Type	Variable	Formula	Rationale
Input	Retained earnings ratio (reea)	(Total earnings after deducting cash dividends) / (average equity)	Represents equity capital internally retained; achieving the same output performance while committing less of this capital reflects efficient capital deployment.
Input	Provisions for loan and lease losses (pfllal)	(Total provisions) / (total outstanding loan and lease receivables, excluding unearned income)	Represents resources set aside for expected credit losses; lower provisioning for a given output level reflects stronger credit−risk management.
Input	Leverage (core capital) ratio (lcc)	(Total core capital) / (adjusted total assets)	Represents core regulatory capital deployed to support operations; achieving output performance with a leaner capital base reflects efficient capital use.
Input	Cash dividends on common stock (cdocs)	(Total cash dividends on common stock) / (average equity capital)	Represents capital distributed to shareholders rather than retained; lower distribution for a given output reflects efficient internal capital allocation.
Output	Return on equity (roe)	Net income / average total equity	Direct measure of shareholder value generation; the primary profitability outcome the model seeks to maximize.
Output	Net interest margin (nim)	(Interest earned−interest paid) / average revenue−generating assets	Captures core lending profitability from intermediation activity; a key income−generation outcome the model seeks to maximize.

Source: Compiled by the author.

Although ROA remained significant throughout the Stage 1 OLS analysis, it was excluded during the Stage 2 DEA variable−reduction step (Section 3.3); ROE and NIM showed stronger discriminating power and were retained as DEA outputs.

3.4. Data sources and sample construction

Data were obtained from the Federal Deposit Insurance Corporation (FDIC) database, which provides standardized annual financial reports for all U.S. insured depository institutions. The initial dataset is comprised of 158,415 institution−year observations. After applying filters for data completeness and the minimum asset threshold of $2 billion, the final sample is comprised of 7,136 annual observations representing 81.2% of the total U.S. depository institution assets throughout the study period. The $2 billion threshold ensures the reporting consistency and aligns the sample with institutions most relevant to systemic stability and regulatory oversight, though it limits direct generalizability to smaller community banks. Institutions were classified by asset size—Small ($2–4B), Medium ($4–10B), Large ($10–250B), Giant (≥$250B)—and by FDIC charter type: OCC−supervised (N), FDIC−regulated non−Fed member (NM), Federal Reserve member (SM), state savings banks (SB), and savings associations (SA).

4. Results and discussion

4.1. OLS regression: components of the relative financial structure

Table 3 presents OLS results for the three profitability models. All demonstrate strong explanatory power: adjusted $R^2 = 0.822$ ($F = 1{,}739.71$, $p < 0.001$), 0.694 ($F = 705.16$, $p < 0.001$), and 0.707 ($F = 716.97$, $p < 0.001$) for ROE, ROA, and NIM, respectively. These results validate H1: the financial structure of depository institutions—captured through a comprehensive set of relative ratios—is a powerful and systematic determinant of performance. Throughout this section, each ratio's combined contribution share is calculated as the sum of its absolute contribution to the sample−mean value of ROE, ROA, and NIM (regression coefficient × mean ratio value, summed in absolute value across the three models), expressed as a percentage of the total across all 28 ratios; it reflects each ratio's weight in the mean profitability level rather than a decomposition of the explained variance (R^2).

Table 3. Regression results for key performance indicators (ROE, ROA, NIM).

Variable	ROE B	t	Sig.	ROA B	t	Sig.	NIM B	t	Sig.
(Constant)	0.07	9.37	***	0.046	18.89	***	0.009	6.9	***
nii	1.326	23.48	***	0.282	36.91	***	−0.576	−52.92	***
cofrga	−0.171	−2.88	**	−0.049	−6.22	***	−0.045	−3.75	***
nie	−0.785	−12.36	***	−0.219	−25.16	***	0.715	57.47	***
reea	0.95	121.91	***	0.065	61.21	***	0.053	35.25	***
ncho	0.479	7.83	***	0.066	7.18	***	0.491	37.43	***
lev	—	—	—	0.003	2.8	**	0.008	7.46	***
pfllal	0.072	13.03	***	0.004	3.86	***	—	—	—
nlal	0.049	6.70	***	0.007	7.58	***	0.012	11.91	***

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Variable	ROE B	t	Sig.	ROA B	t	Sig.	NIM B	t	Sig.
lcc	−0.285	−14.75	***	—	—	—	0.036	9.73	***
oass	−0.22	−7.97	***	−0.043	−11.55	***	−0.042	−8.17	***
ibde	−0.042	−7.05	***	−0.007	−6.9	***	−0.012	−9.02	***
tlia	—	—	—	−0.047	−18.7	***	—	—	—
uclin	3.856	12.98	***	0.465	11.58	***	0.532	9.28	***
adf3mol	—	—	—	1.195	6.78	***	2.084	36.95	***
ainas	−1.242	−18.52	***	0.979	5.63	***	0.348	8.23	***
lsfreuns	0.92	6.37	***	0.203	11.02	***	0.089	2.9	**
cdocs	0.044	21.59	***	0.006	21.55	***	0.009	22.08	***
Adj. R^2	0.822			0.694			0.707		
F−stat	1739.71	p<0.001		705.16	p<0.001		716.97	p<0.001	

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; —indicates variable not retained in this model. Only selected variables shown for brevity; full results available on request. Source: Compiled by the author.

The retained earnings (reea) is the strongest and most consistent positive driver across all three models (ROE: B = 0.950, t = 121.91; ROA: B = 0.065, t = 61.21; NIM: B = 0.053, t = 35.25; all $p < 0.001$), contributing 2.9% of the combined contribution share. This confirms that internally generated capital retention signals both financial strength and management quality (Myers and Majluf, 1984). Net loans and leases (nlal, 3.6% combined contribution share) is the largest single positive contributor, consistent with the financial intermediation theory (Sealey and Lindley, 1977; Allen and Santomero, 2001). Risk−related variables—assets delinquent 3+ months, uncollected loan income, provisions, and net charge−offs—show positive associations, reflecting proactive credit risk recognition in well−managed institutions (Beatty and Liao, 2011; Berger and DeYoung, 1997).

Reea, cdocs, nii, nie, and cofrga share accounting components with their respective dependent variables (e.g., reea's t = 121.91 on ROE, the largest in Table 3), partly explaining their large t−statistics. Excluding these predictors reduces adjusted the R^2 to 0.30 (ROE), 0.28 (ROA), and 0.39 (NIM), confirming that part of the original fit reflects the accounting−identity overlap. Nonetheless, they are retained in the 28−ratio structure, consistent with the study's descriptive aim of characterizing co−movement rather than isolating independent causal drivers; the remaining 28–39% indicates a genuine structural association beyond this overlap.

Total liabilities (tlia, 20.4% combined negative contribution share; ROA: B = −0.047, t = −18.70, $p < 0.001$) is the single largest negative contributor, consistent with leverage being associated with lower asset−based profitability (Diamond and Rajan, 2000). Noncurrent loans and leases (5.6%) and interest−bearing deposits (4.2%) follow. The non−interest expense (nie, 7.1% combined contribution share) exhibits the most striking context−dependent pattern: negative for ROE (B = −0.785) and ROA (B = −0.219) but strongly positive for NIM (B = 0.715, t = 57.47, $p < 0.001$). This divergence reflects the dual nature of operating expenditure in banking—while higher costs are associated with lower bottom−line returns in the short term, institutions strategically investing in the credit origination capacity, relationship management, and loan monitoring tend to record higher interest income streams (Berger and Mester, 1997; Rogers, 1998).

Figure 1 illustrates the directional impact of the seven most influential financial ratios on the three profitability indicators, with the combined contribution of the remaining 21 significant ratios grouped as "Other factors"; Figure 2 presents the absolute percentage impact of all 28 ratios individually. Collectively, these figures indicate that no single ratio dominates the profitability determination: total liabilities accounts for the largest individual share (20.4%) of the combined contribution share, yet several ratios—most notably non−interest expense—exert opposing directional effects across ROE, ROA, and NIM. This pattern supports H1's claim that profitability is shaped by the configuration of the broader financial structure rather than by any single ratio in isolation. Furthermore, balance−sheet composition ratios (total liabilities, noncurrent loans and leases, nonaccrual assets, interest−bearing deposits, and net loans and leases) collectively account for the majority of the combined impact among the seven most influential ratios (38.8 of 50.2 percentage points), exceeding the contribution of the two income−statement items (non−interest expense, non−interest income) also present among the top ratios.

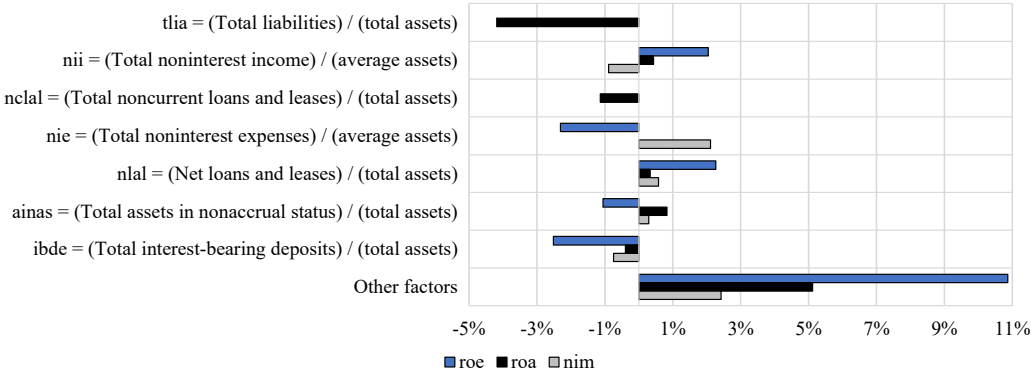


Figure 1. Directional impact of key financial ratios on profitability indicators (ROE, ROA, NIM), 2000 to September 2020. Source: Compiled by the author.

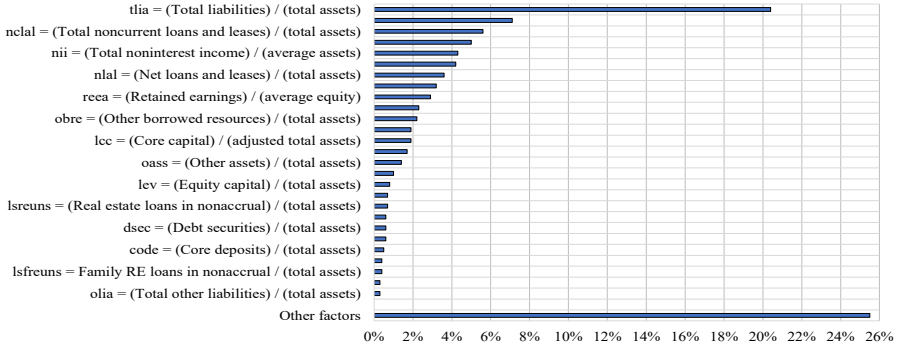


Figure 2. Absolute percentage impact of each financial ratio on combined profitability indicators. Source: Compiled by the author. Note: Bars show each ratio's combined contribution share, calculated as the sum of its absolute contribution to the sample−mean value of ROE, ROA, and NIM (see Section 4.1), expressed as a percentage of the total across all 28 ratios.

4.2. DEA efficiency assessment: overall classification

The VRS DEA model classified all 7136 institution−year observations into four groups (Figure 3): Group A (Near−Frontier, rounded 100%, 185 cases, 2.6%); Group B (Excellent, 84–99%, 2252 cases, 31.6%); Group C (Medium, 65–83%, 2405 cases, 33.7%); Group D (Low, 0–64%, 2294 cases, 32.1%); and an overall average of 71.4%. Of the 185 Group A observations, 170 have θ exactly equal to 1.000; the remaining 15 have θ marginally exceeding 1.000. A slack evaluation for these observations was not conducted in this study. The efficient institutions (Groups A and B) display elevated non−interest expenses, high retained earnings and net loan ratios, and low interest−bearing deposit ratios—the inverse of inefficient institutions (Groups C and D). Because reea is strongly positively associated with ROE and NIM (Table 3), institutions with high retained−earnings ratios typically also generate proportionally higher outputs; input−oriented DEA efficiency is a relative, frontier−based concept, so a DMU can be classified as efficient with an above−average input level, provided no peer combination achieves its same output using less of every input. This reconciles the finding that efficient institutions (Groups A/B) display higher average reea with reea's classification as an input. The recommendation to rebuild retained earnings follows from this descriptive cross−group comparison and from reea's role as a profitability driver in Stage 1, not from a computed DEA input−reduction path, which the manuscript does not report.

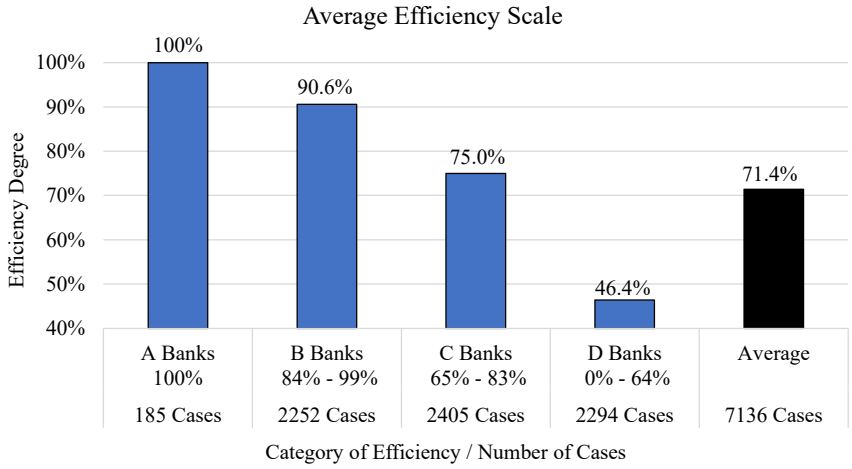


Figure 3. Classification of U.S. depository institutions by efficiency group. Source: Compiled by the author.

Two particularly noteworthy findings emerge from the classification. First, non−interest expenses are systematically higher in Groups A and B than in C and D—a descriptive association that diverges from the conventional assumption that cost minimization is the primary route to efficiency, though it does not directly test that paradigm, as a non−interest expense is not among the DEA inputs in the present profitability−oriented specification. Efficient institutions strategically invest in technology, human capital, and governance—all reflected in higher non−interest expenses—consistent with Berger and Mester (1997) and Fiordelisi et al. (2011). Thus, rising operating costs may signal organizational transformation rather than inefficiency (Rogers, 1998;

Koetter et al., 2012). Second, core capital ratios are highest in Group A but higher in Group D than Group B, breaking the monotonic capitalization–efficiency relationship that underpins Basel−based regulatory logic. This is consistent with Hoffman (2010) and the argument that excessive capitalization is associated with constrained growth rather than necessarily reflecting prudent management. These findings provide strong empirical support for H3 and H4.

4.3. Efficiency dynamics across time (2000–2020)

Figure 4 reveals three distinct efficiency phases over the study period. The pre−crisis period (2000–2007) recorded moderate−to−high efficiencies (peak: 76.7% in 2000), characterized by relatively low ratios of delinquent real estate loans, nonaccrual family real estate loans, and nonaccrual nonfarm nonresidential property loans—indicators of contained credit risk exposure. The crisis period (2008–2010) produced the most severe efficiency deterioration in the sample: the average efficiency reached its nadir at 57.9% in 2009, declining from 62.0% in 2008, and only partially recovering to 61.1% in 2010. This trough coincides with simultaneous spikes in noncurrent loans, nonaccrual assets, provisions, and equity−to−asset ratios, alongside sharp declines in net loans and leases and retained earnings—consistent with the bad management hypothesis (Berger and DeYoung, 1997). The post−crisis recovery period (2011–2020) shows a gradual but sustained improvement, culminating in a peak efficiency of 78.1% in 2019—the highest level in the entire sample period, reflecting progressive balance sheet repair and rebuilding of retained earnings.

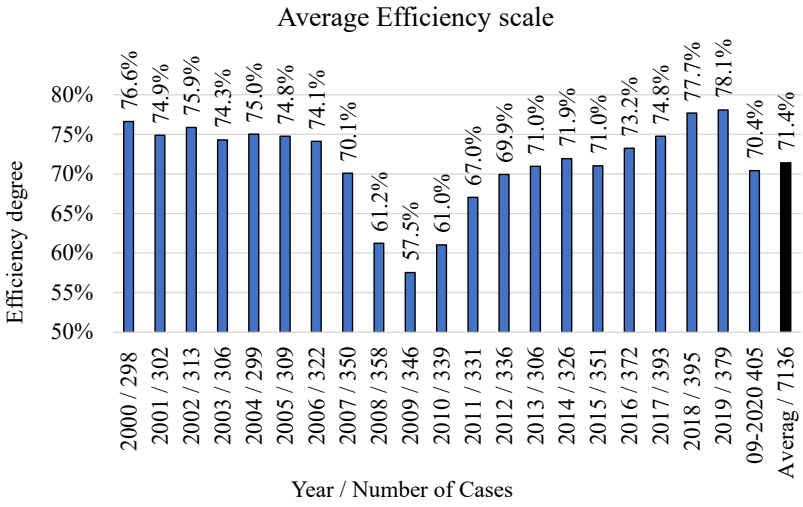


Figure 4. Average efficiency of U.S. depository institutions by year, DEA results (2000–September 2020). Source: Compiled by the author.

4.4. Efficiency by charter classification

Figure 5 presents the average efficiency scores by FDIC charter type. NM banks—state−chartered, non−Federal Reserve member institutions regulated directly by the FDIC—record the highest average efficiency (73.3%), reflecting the operational flexibility of their regulatory classification and typically

diversified commercial banking activities. N banks (OCC−supervised) and SM banks (Federal Reserve member) record intermediate efficiency levels (72.6% and 72.3%, respectively).

Savings banks (SB, 64.0%) and savings associations (SA, 67.3%) record the lowest efficiency and are also the least numerous in the sample. Their underperformance is associated with a distinctive financial profile: elevated ratios of interest−bearing deposits, provisions for loan and lease losses, equity−to−total assets, debt securities, and loans secured by family real estate—including nonaccrual family real estate exposures. This configuration reflects the historical concentration of savings institutions in mortgage lending, which is associated with a heightened sensitivity to real estate cycles and narrower income diversification (DeYoung and Roland, 2001). The finding confirms the need for charter−sensitive efficiency benchmarks in supervisory frameworks.

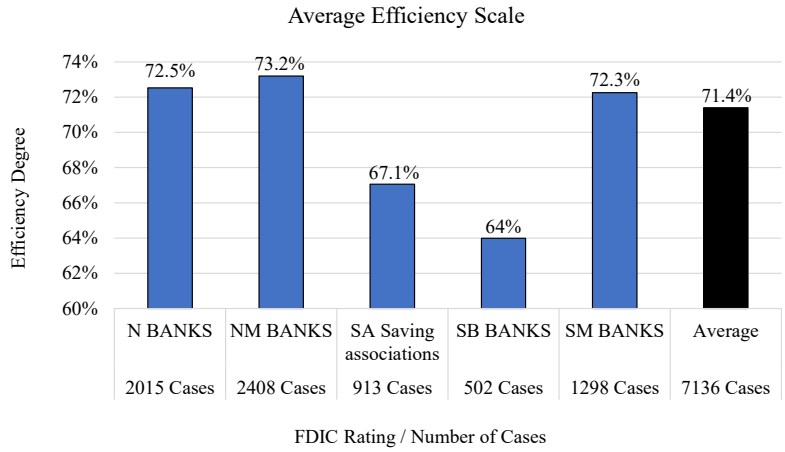


Figure 5. Average efficiency of U.S. depository institutions by FDIC charter classification. Source: Compiled by the author.

4.5. Efficiency by asset size: average efficiency differences across size categories

Figure 6 presents the efficiency scores by asset size, revealing a non−linear relationship that diverges from the conventional economies−of−scale hypothesis. The efficiency ordering—Large (72.1%) > Small (71.7%) > Medium (70.6%) > Giant (69.3%)—indicates that efficiency does not monotonically increase with asset size, providing further support for H2.

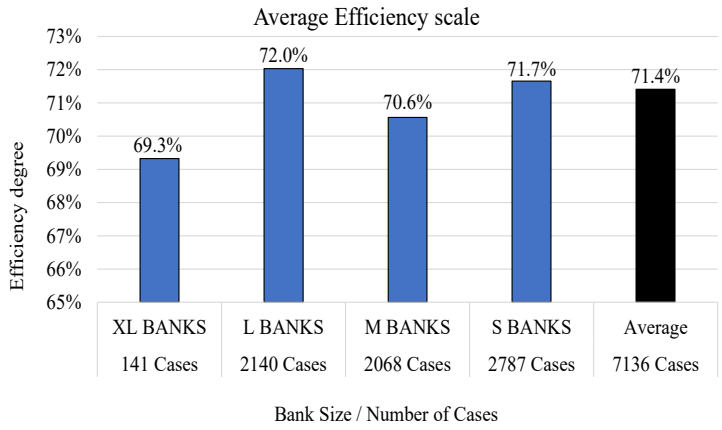


Figure 6. Average efficiency of U.S. depository institutions by asset size. Source: Compiled by the author.

Large banks ($10 – 250B, 2,140 cases) record the highest efficiencies, a pattern associated with diversified income streams, low nonaccrual asset ratios, and effective credit risk management. Giant banks (≥$250B, 141 cases) record the lowest efficiencies despite their resource advantages and systemic importance. Their structural profile is characterized by the following pattern: low ratios of net loans and leases, time and savings deposits, core capital to adjusted total assets, and net interest margin, combined with high ratios of loans secured by real estate delinquent for three or more months, debt securities, and other assets. This configuration suggests that organizational complexity is associated with coordination costs and asset allocation inefficiencies that may offset scale advantages—a pattern consistent with, though not formally establishing, diseconomies of scale (Hughes and Mester, 2013); a rigorous test would require decomposing VRS from CRS efficiency to derive the scale efficiency, which was not conducted in this study. Small banks ($2–4B, 2,787 cases) record higher efficiencies than medium banks ($4–10B, 2,068 cases), consistent with relationship−banking models that support tighter credit monitoring and lower delinquency ratios (Berger and Udell, 2002). Both small and medium banks share structural vulnerabilities including low noninterest income ratios and elevated interest−bearing deposit ratios.

4.6. The empirically benchmarked relative financial structure and monitoring model

The convergence of OLS regression results and DEA efficiency classification enables the construction of an empirically grounded relative financial structure (Table 4), with calibrated empirical benchmark margins derived from Groups A and B, and limiting thresholds derived from Group C. This framework encompasses 28 financial ratios spanning capital adequacy, asset quality, funding structure, income generation, and operating efficiency.

Table 4. Proposed monitoring model: empirically benchmarked relative financial structure for U.S. depository institutions. (Performance targets: NIM 4.3%–6.7% (min 3.7%); ROA 1.5%–2.7% (min 1.1%); ROE 13.8%–21.8% (min 11.4%)).

Rel. Imp.	Financial ratio	Abbr.	Benchmark margin	Limit
20.4%	(Total liabilities) / (total assets)	tlia	86.1%–88.5%	***
7.1%	(Total noninterest expenses) / (average assets)	nie	***	nie ≤ 4.8%
5.6%	(Total noncurrent loans and leases) / (total assets)	nclal	***	nclal ≤ 1.6%
5.0%	(Total assets in nonaccrual status) / (total assets)	ainas	***	ainas ≤ 0.8%
4.3%	(Total noninterest income) / (average assets)	nii	1.8%–4.0%	nii ≥ 1.5%
4.2%	(Total interest−bearing deposits) / (total assets)	ibde	53.9%–59.0%	***
3.6%	(Net loans and leases) / (total assets)	nlal	59.1%–64.0%	nlal ≥ 46.1%
3.2%	(Time and savings deposits) / (total assets)	tsde	56.7%–65.6%	***
2.9%	(Retained earnings) / (average equity)	reea	6.3%–10.4%	reea ≥ 4.6%
2.3%	(Assets delinquent 3+ months) / (total assets)	adf3mol	***	adf3mol ≤ 0.8%
2.2%	(Other borrowed resources) / (total assets)	obre	***	obre ≤ 14.2%
1.9%	(Uncollected loans income) / (total assets)	uclin	***	uclin ≤ 5.0%
1.9%	(Core capital) / (adjusted total assets)	lcc	9.9%–12.8%	lcc ≥ 8.7%
1.7%	(Provisions for loan losses) / (total loans)	pfllal	6.4%–12.4%	pfllal ≤ 28.7%
1.4%	(Other assets) / (total assets)	oass	3.6%–5.0%	***
1.0%	(Net charge−offs) / (average loans)	ncho	***	ncho ≤ 2.0%
0.8%	(Equity capital) / (total assets)	lev	14.4%–17.8%	lev ≤ 29.7%
0.7%	(Goodwill and other intangibles) / (total assets)	gaoi	1.9%–2.2%	***
0.7%	(Real estate loans in nonaccrual) / (total assets)	lsreuns	***	lsreuns ≤ 0.6%
0.6%	(RE loans delinquent 3+ months) / (total assets)	lsred3mol	***	lsred3mol ≤ 0.3%
0.6%	(Debt securities) / (total assets)	dsec	16.7%–18.7%	dsec ≤ 20.0%
0.6%	(Interest expenditure) / (income−generating assets)	cofrga	***	cofrga ≤ 1.8%
0.5%	(Core deposits) / (total assets)	code	46.2%–62.4%	***
0.4%	(Cash dividends on common stock) / (average equity)	cdocs	8.8%–10.1%	***
0.4%	Family RE loans in nonaccrual / (total assets)	lsfreuns	***	lsfreuns ≤ 0.3%
0.3%	(Loans secured by family real estate) / (total assets)	lsbfrs	15.2%–18.0%	lsbfrs ≤ 19.7%
0.3%	(Total other liabilities) / (total assets)	olia	1.5%–2.9%	***
0.0%	Nonfarm nonresidential loans nonaccrual / assets	lsnnpuns	***	lsnnpuns ≤ 0.1%
25.5%	Other factors	***	***	***

Note: *** indicates no specific threshold defined for this variable. Rel. Imp. denotes each ratio's combined contribution share as defined in Section 4.1. Benchmark margins derived from Groups A and B; ratio limits derived from Group C. Source: Author's calculations.

Theoretically, this framework advances the conceptualization of bank efficiency from a single−dimensional construct to a multidimensional emergent property of the integrated financial structure, consistent with systems theory perspectives (Allen and Santomero, 2001) and recent calls for holistic regulatory approaches (Borio and Drehmann, 2009; Josef et al., 2025). It extends the

financial intermediation theory (Sealey and Lindley, 1977) by demonstrating that the efficiency frontier is defined not by any single ratio but by the simultaneous optimization of capital productivity, loan quality, funding composition, and strategic cost deployment.

Practically, unlike stress test frameworks focused on worst−case capital depletion scenarios (Roy, 2024), the proposed model monitors the ongoing configuration of institutional balance sheets and income statements; whether this enables earlier detection of efficiency deterioration is a testable proposition requiring temporal, out−of−sample validation not conducted in this study. The consistency of structural efficiency patterns across all four size categories and five charter types descriptively supports H3 within this sample; formal tests of parameter stability across groups were not conducted, and institutions below the $2 billion threshold were not examined, so generalizability beyond the sampled population remains to be established. H1 is supported—the 28−ratio structure is associated with 69.4–82.2% of profitability variance (28–39% after excluding mechanically related predictors), indicating a genuine structural association. H2 is confirmed—systematic structural differences distinguish Groups A/B from C/D across all ratio categories. H3 is descriptively supported within the sampled population—consistent structural efficiency patterns hold across all four size categories and five charter types examined, though formal parameter−stability tests were not conducted and institutions below $2 billion were excluded. H4 is partially supported: core capital ratios exhibit a non−monotonic relationship with DEA efficiency (Section 4.2), and a direct comparison confirms only weak agreement between a capital−ratio−only classification (median split on lcc) and the DEA−based efficiency grouping ($\varphi = 0.17$, Cohen's $\kappa = 0.16$, $\chi^2(1) = 210.5$, $p < 0.001$), indicating only slight agreement by conventional benchmarks (Landis and Koch, 1977). This indicates that capital−ratio benchmarking alone only captures a limited share of the structural variation identified by the DEA−based framework, though this in−sample comparison does not by itself establish superior out−of−sample predictive performance.

5. Conclusions

This study assessed U.S. depository institutions (2000–2020) using a sequential OLS–DEA methodology applied to 7136 institution−year observations representing 81.2% of the total sector assets. The principal findings advance both the theoretical understanding and practical regulation of bank efficiency. Twenty−eight financial ratios collectively explain 69.4–82.2% of institutional profitability variance (28–39% after excluding mechanically related predictors), with retained earnings, net loans and leases, and total liabilities accounting for 26.9% of the combined contribution share. Efficient institutions exhibit consistent structural profiles—higher non−interest expenses, stronger retained earnings, greater net loan ratios—that hold across institutional sizes and charter types. Three findings directly challenge the established regulatory assumptions: higher non−interest expenses in efficient banks diverge from, though do not directly test, the cost−minimization paradigm, since a non−interest expense is not a DEA input in this profitability−oriented specification; non−monotonic core capital ratios undermine the Basel presumption that higher capitalization reliably signals better performance; and the efficiency ordering Large > Small > Medium > Giant is consistent with, though does not formally establish, diseconomies of scale.

The study offers several practical recommendations. For regulatory authorities, the following are recommended: adopt the proposed 28−ratio monitoring model as a complement to capital adequacy frameworks; treat elevated non−interest expenses as potential strategic investment indicators rather

than efficiency warnings; monitor retained earnings as a primary monitoring indicator; and apply charter−sensitive benchmarks that account for savings institutions' structural mortgage concentration. For bank managers, the following are recommended: prioritize structural optimization over asset growth; rebuild retained earnings through a disciplined dividend policy and profit reinvestment; reduce reliance on interest−bearing deposits; expand net loan ratios toward the empirically identified benchmark range of 59.1–64% of total assets; and strategically invest in credit origination, relationship management, and risk monitoring capabilities. Giant banks, in particular, should reorient balance sheets toward core lending activities and away from debt securities and other non−earning assets.

Several limitations warrant acknowledgment. The $2 billion asset threshold excludes the majority of U.S. depository institutions by number—primarily community banks and credit unions—limiting direct generalizability to smaller institutions. DEA's deterministic nature attributes all frontier deviations to inefficiency without accounting for random measurement errors, macroeconomic shocks, or exogenous regulatory changes. The pooled cross−sectional treatment does not fully exploit the panel structure of the data, and the proposed model requires recalibration for non−U.S. regulatory environments. Additionally, the sequential design entails a structural circularity: ratios are selected via their association with ROE, ROA, and NIM, two of which then serve as DEA outputs, and the resulting efficiency groups are, in turn, used to define the benchmark ranges in Table 4; independent validation via a temporal holdout sample, rather than the in−sample comparison conducted here, is required before these benchmarks can be treated as validated thresholds.

Future research should explore the following: extend the framework to institutions below $2 billion; integrate dynamic DEA or SFA with panel data methods for unobserved heterogeneity control; investigate the precise size threshold at which diseconomies emerge through quantile DEA; validate the monitoring model through out−of−sample testing and stress scenario simulation; and conduct cross−country comparative studies to assess the generalizability of the empirically benchmarked financial structure concept across regulatory regimes.

Author contributions

Jalal Hafeth Ahmad Abu−alrop: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing—original draft, Writing—review & editing.

Use of AI tools declaration

The author declares they have used Artificial Intelligence (AI) tools in the creation of this article. AI tools used: Claude (Anthropic). How were the AI tools used: Language editing and manuscript formatting assistance. The AI tool was not used for data collection, analysis, interpretation, or generation of research findings.

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Data availability statement

The data underlying this study are drawn from the publicly available FDIC database (https://www.fdic.gov/bank/statistical/). The processed dataset has been deposited on Harvard Dataverse and is available at https://doi.org/10.7910/DVN/JYHLQP.

Conflict of interest

The author declares no conflicts of interest in this paper.

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