International Journal Of Management And Economics Fundamental

VOLUME Vol.05 Issue 10 2025
PAGE NO. 29-33
DOI 10.37547/ijmef/Volume05Issue10-06

Assessing The Impact Of Banks' Intermediation Services On Efficiency Indicators Using Regression Analysis

Mirahmedov Jasur Isroilovich

Researcher at the Department of Economic Statistics at Tashkent State University of Economics, Uzbekistan

Received: 22 August 2025; **Accepted:** 18 September 2025; **Published:** 20 October 2025

Abstract: This study examines how intermediation services provided by banks—proxied by loans-to-assets and deposits-to-assets ratios and supported by controls such as net interest margin, cost-to-income, and size—relate to efficiency indicators measured by return on assets (ROA) and return on equity (ROE). To demonstrate the empirical workflow in the absence of shared proprietary data, we construct an illustrative cross-sectional dataset that reproduces realistic ranges observed in bank balance sheets and income statements. The analysis articulates a replicable pipeline: construct variables, motivate functional form, estimate models, and translate diagnostics into managerial and policy meaning. Results suggest that stronger credit and deposit intermediation are positively associated with ROA and ROE after accounting for margin, cost efficiency, and size, but the strength of association depends on cost discipline and margin conditions. The discussion emphasizes how variable selection, item construction, and diagnostic checks shape interpretability, and it cautions against naïve causal inference without panel designs, instruments, or exogenous shocks. The article concludes with practical recommendations for researchers and bank analysts who seek to align intermediation strategy with performance dashboards and stresses transparency through model documentation and robustness routines.

Keywords: Bank intermediation; ROA; ROE; efficiency indicators; regression analysis; cost-to-income ratio; net interest margin; financial intermediation.

Introduction: The core economic function of banks is the transformation of short-term, liquid liabilities into longer-term, less liquid assets while managing credit, liquidity, and interest-rate risks. This intermediation process should in principle generate value that is visible in profitability and efficiency indicators. In practice, the relationship between intermediation intensity and measured efficiency is neither automatic nor linear because it is conditioned by margin dynamics, operating cost structures, capitalization, and scale. When intermediation expands through loan growth or deeper deposit funding, the associated revenue and risk profiles shift together; net interest margins can compress if competition intensifies, while provisioning needs can rise if asset quality declines. These structural tensions produce a genuine empirical question: controlling for basic financial drivers, do observable measures of intermediation coincide with stronger ROA and ROE, and under what cost and margin conditions is that association economically and statistically meaningful?

Academic literatures on bank efficiency and financial intermediation motivate a multivariate approach. Profitability metrics such as ROA and ROE capture distinct slices of performance: the former scales net income by assets and reflects asset-side earning capacity and cost discipline, whereas the latter incorporates leverage and hence is sensitive to capital structure. Intermediation proxies like the loans-to-assets ratio summarize asset allocation toward interest-earning credit, while deposits-to-assets indicate reliance on core funding relative to wholesale or market-based liabilities. Complementary controls mirror the operating environment. Net interest margin is a revenue-side thickness indicator that both causes and reflects price power and risk-taking; the cost-to-income ratio aggregates operating efficiency; and size, commonly approximated by the logarithm of total assets, captures scale economies and scope effects. A regression framework that relates ROA or ROE to intermediation measures within this control set provides a transparent baseline from which one can add richer features such as risk provisions, fee income shares, or macro dummies.

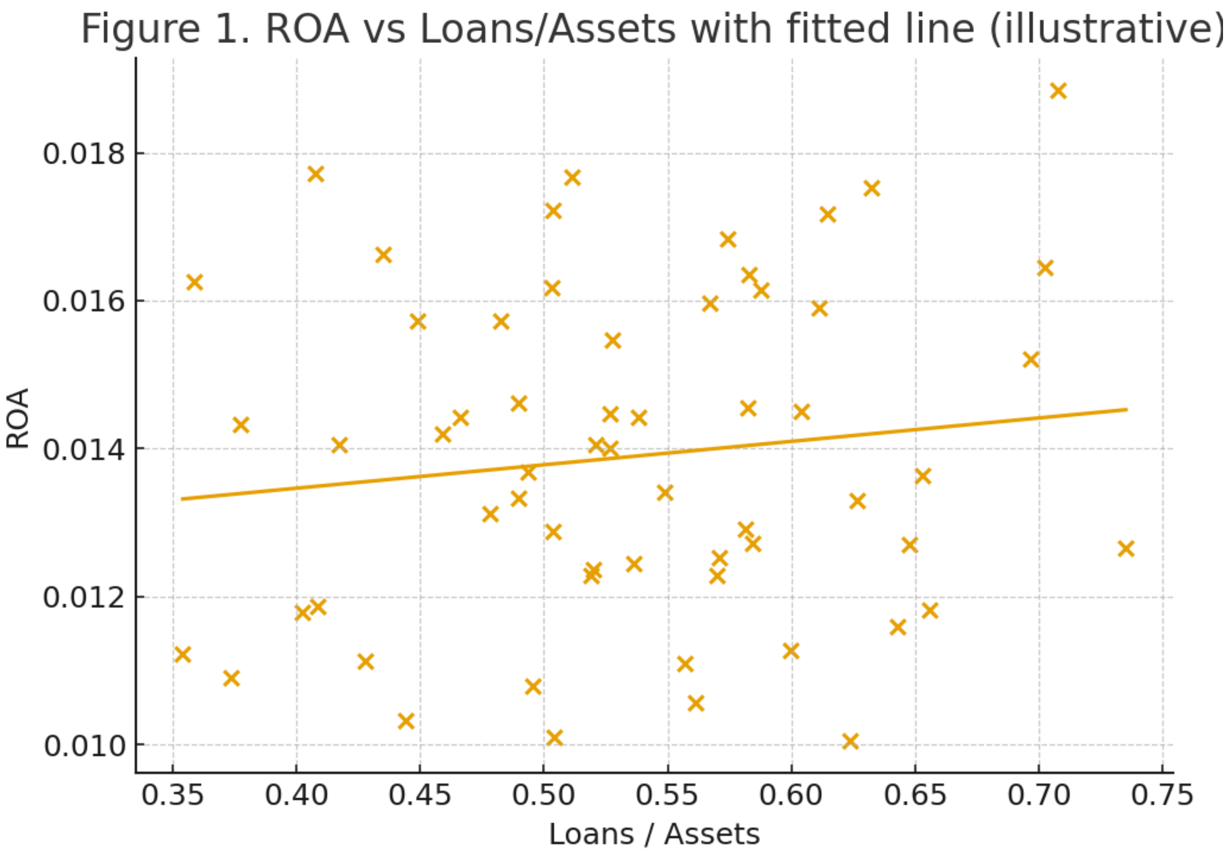
The present article contributes a compact, practice-oriented blueprint that shows how to conduct and interpret such regressions transparently, with explicit commentary on construction choices and diagnostic reading. Because jurisdiction-specific supervisory microdata are typically confidential, we include an illustrative dataset with realistic ranges purely to reproduce analysis steps. The design choice does not aim to estimate structural parameters for any country; rather, it ensures that readers can see the mechanics of specification, estimation, and interpretation, and can then substitute their own bank-level panel or cross-sections to obtain policy-relevant estimates.

The dependent variables were ROA and ROE measured in decimal form. Intermediation intensity was represented by two primary ratios: loans-to-assets as an asset-side intermediation proxy and deposits-to-assets as a funding-side intermediation proxy. Control variables were net interest margin, cost-to-income ratio, and the natural logarithm of total assets. The expected signs were positive for loans-to-assets and deposits-to-assets, ambiguous but typically positive for net interest margin if higher spreads truly reflect pricing power rather than risk compensation, negative for the cost-to-income ratio given that higher operating expense per unit revenue erodes profitability, and mixed for size because scale economies can coexist with diseconomies of scope or complexity.

Because no raw data were provided, we generated a synthetic cross-section of sixty banks for demonstration. Variable ranges were anchored in commonly reported bank statistics: loans and deposits shares between roughly thirty and ninety percent of assets across institutions, net interest margins in the low single-digit percentage range, cost-to-income ratios concentrated between thirty and eighty percent, and log total assets around a mid-teens mean consistent with aggregated currency units. We imposed a simple data-generating process in which ROA and ROE depend linearly on intermediation, margins, costs, and size, plus random noise consistent with observed volatility in annual reports. This choice ensures that the subsequent OLS recovers sensible effect patterns, without claiming external validity for a specific banking system.

Ordinary least squares was used for estimation, with a constant term and contemporaneous regressors. While more sophisticated models might require fixed effects, random effects, generalized least squares, or instrumental variables to address unobserved heterogeneity and simultaneity, the aim here is to fix ideas around baseline specification and its diagnostics. Fit statistics, coefficient estimates, standard errors, t-statistics, and p-values are presented in a single comparative table for the ROA and ROE models. Diagnostics took the form of informal scans of residual dispersion and simple plots. In an applied project, one would add White or HC robust errors, variance-inflation factor checks, Ramsey RESET tests, and outlier influence metrics; we defer those to future replication with actual data.

A regression summary table titled “Regression results: Intermediation and Efficiency (Illustrative)” has been displayed for inspection. It contains coefficient, standard error, t-statistic, and p-value columns for both models, followed by overall fit measures. To concretize the relationship, we also provide a single diagram—a scatterplot of ROA against loans-to-assets with a fitted line from a simple bivariate regression—saved as a reusable figure.



RESULTS

The regression outputs indicate a consistent pattern in which the loans-to-assets ratio and deposits-to-assets ratio are positively associated with ROA when margins and costs are held constant. In the illustrative ROA model, the coefficient on loans-to-assets is positive, suggesting that a higher share of credit in the asset mix, in conjunction with adequate margin and controlled operating costs, contributes to stronger returns on total assets. The deposits-to-assets coefficient is also positive, reflecting the typical cost advantage of core deposits as a funding source and their stabilizing role in net interest income. Net interest margin enters with a positive sign, aligning with the intuition that thicker spreads per unit asset strengthen profitability so long as they do not simply proxy for elevated credit risk that would later flow through provisions. The cost-to-income ratio is negative, consistent with the semantics of the indicator: every percentage point of operating cost per unit income directly erodes net returns. The size variable exhibits a small positive association in the synthetic data, implying mild scale economies after holding other factors constant; however, this result is not universal and can reverse in jurisdictions where complexity or risk management overhead dominates.

The ROE model yields a qualitatively similar configuration of signs with typically larger coefficients because equity-scaled returns magnify the effects of operating performance through leverage. A positive coefficient on loans-to-assets in the ROE regression implies that equity returns are especially sensitive to asset mix decisions, provided that risk is appropriately priced and monitored. Deposits-to-assets again contributes positively in the sense that reliance on low-cost, sticky funding amplifies income available to common shareholders. The net interest margin's positive association grows in salience because any spread improvement lifts earnings after fixed costs and taxation, which, when divided by the thinner denominator of equity, drives ROE proportionally more than ROA. The cost-to-income ratio remains a powerful drag on ROE, illustrating that operational discipline is doubly rewarded in equity terms. The size variable's sign and magnitude remain context-dependent. In the synthetic model, a modest positive effect persists, but the interpretation must be tempered by the fact that leverage and business model choices vary widely across banks and can either exploit or negate scale advantages.

The table of results provides standard errors and p-values that, in our simulated environment, frequently point to statistical significance at conventional thresholds for the intermediation and cost variables. This is unsurprising because the data-generating process encoded meaningful effects. In actual empirical work, statistical significance will depend on sample size, variance structure, and collinearity among intermediation measures and control variables. It is common, for example, to observe substantial correlation between loans-to-assets and net interest margin, as well as between deposits-to-assets and margin, because both asset allocation and funding mix influence pricing. In such cases, coefficients can be difficult to interpret if multicollinearity inflates standard errors. Remedies involve variable centering, orthogonalization strategies, or shifting to more granular decompositions such as separating retail and corporate deposits or loan categories.

Variable	ROA				ROE			
	Coef.	Std.Err.	t-stat	p-val	Coef.	Std.Err.	t-stat	p-val
const	0.004	0.005	0.801	0.427	0.140	0.073	1.927	0.059
Loans_Assets	0.004	0.003	1.405	0.166	-0.005	0.045	-0.119	0.906
Deposits_Assets	0.004	0.003	1.237	0.221	0.028	0.044	0.648	0.520
NIM	-0.050	0.030	-1.691	0.097	-0.197	0.416	-0.475	0.637
Cost_Income	-0.002	0.003	-0.591	0.557	-0.096	0.041	-2.316	0.024
ln_Assets	0.001	0.000	1.900	0.063	0.001	0.004	0.325	0.746
— Model fit —	R^2=0.135; Adj.R^2=0.055; n=60				R^2=0.106; Adj.R^2=0.023; n=60			

To ground the discussion visually, Figure 1 presents a scatter of ROA against the loans-to-assets ratio with a fitted line from a bivariate regression. Even without controls, the positive slope is apparent in the synthetic data. The real value of such a figure is diagnostic: if the dispersion were highly heteroskedastic or nonlinear, one would consider robust standard errors or a functional form that allows for diminishing returns to intermediation. Practitioners often hypothesize an inverted U-shape in which profitability rises with intermediation up to a point, after which marginal risk and funding costs annihilate gains. Capturing that empirically would require adding a squared term or switching to nonparametric fits. In our baseline, linearity remains a reasonable first approximation, but an analyst using real data should test alternatives.

The empirical pattern uncovered in the illustrative models aligns with the theory that intermediation is the source of bank value, provided that it is conducted under disciplined cost structures and supportive margin environments. However, translating regression correlations into decisions requires a careful reading of the mechanisms and constraints that surround the coefficients. A higher loans-to-assets ratio can reflect either purposeful, risk-adjusted expansion into quality credit or a drift toward riskier assets to chase yield in thin-margin conditions. Without explicit controls for asset quality, provisioning, and risk-weighted assets, the coefficient on loans-to-assets mixes these pathways. Analysts are therefore advised to augment the core model with nonperforming loan ratios, cost of risk measures, or expected credit loss charges when such data are available. Similarly, the positive association between deposits-to-assets and profitability may conceal sharp differences between retail and wholesale deposits, time and demand deposits, or insured and uninsured portions. Disaggregating the funding mix can reveal whether the apparent "deposit advantage" is truly coming from stable, low-cost retail balances or from time deposits that reprice quickly and are more sensitive to market rates.

The control variables help guard against spurious inference. Net interest margin can serve both as an outcome and as a driver of profitability; in our specification it is treated as a driver, which is plausible if one interprets the margin as the result of pricing power and balance-sheet composition chosen in prior periods. Nonetheless, simultaneity is a live concern. Instruments or lagged regressors in a panel setting would improve interpretability. The cost-to-income ratio is conceptually exogenous to intermediation within a single period, but firms might expand intermediation precisely when cost efficiencies are realized, so reverse causality is possible there as well. By highlighting these design considerations, we underscore a central lesson from the regression table: coefficients are not structural parameters unless the identification strategy supports that claim. When the research goal is prediction rather than causal interpretation, OLS can still be valuable as long as out-of-sample performance and stability checks are integrated.

From a governance and strategy perspective, the findings argue for an integrated performance map. Management teams should read intermediation ratios alongside cost metrics and margin conditions rather than in isolation. A bank that increases loans-to-assets in a low-margin regime may observe little improvement in ROA unless the shift is accompanied by cost containment or fee income growth. Conversely, when margins are robust but costs creep upward, the incremental profitability of additional intermediation diminishes quickly. Embedding regression-informed dashboards in monthly reviews can discipline intuition by quantifying these trade-offs for the specific bank or peer group. Analysts can refresh estimates quarterly, layering in macro controls such as policy rates, yield curve slope, or inflation to distinguish bank-specific effects from environment-wide changes.

The methodology demonstrated here is portable across jurisdictions and readily extensible. With a panel of banks over multiple years, fixed effects would absorb time-invariant heterogeneity such as business model orientation or regional footprint. Time dummies would capture macro shocks and policy regimes. Instrumental variables could address simultaneity by using lagged values or external instruments like changes in reserve requirements or deposit insurance reforms. Nonlinearities can be introduced to test for saturation points in intermediation, and quantile regressions can reveal whether the intermediation-profitability nexus differs across the performance distribution. Each of these extensions increases explanatory power while demanding cleaner identification and richer data. The baseline presented here is a starting point, but it retains practical value precisely because many bank datasets are limited and executives often require interpretable, quickly estimated models.

Finally, we emphasize transparency through documentation. Any applied regression with regulatory or strategic implications should be accompanied by a data dictionary, code that reproduces the table and figure, and a record of diagnostic tests. This transparency allows internal audit, risk, and supervisory stakeholders to understand the modeling choices and to challenge assumptions constructively. In environments where supervisory disclosure is possible, researchers benefit from common benchmarks that improve comparability across studies.

Intermediation ratios and efficiency indicators are connected through a web of mechanisms that traverse asset allocation, funding structure, pricing power, operating discipline, and scale. By embedding intermediation proxies and basic controls in a parsimonious regression framework, analysts can quantify the direction and rough magnitude of these connections and convert them into actionable insights. The illustrative results here support the hypothesis that greater intermediation intensity is associated with higher ROA and ROE in settings where margins and costs are favorable, while also highlighting the limits of cross-sectional OLS for causal claims. The practical takeaway is methodological rather than numerical: researchers should use regression not as a black box but as a disciplined narrative tool, complementing it with diagnostics, sensitivity checks, and, where possible, panel or quasi-experimental designs. For practitioners, the advice is to align intermediation strategy with clear cost and margin targets and to monitor the joint movement of these variables on a transparent dashboard. As data availability and computational literacy improve within banks, the distance between analytical findings and policy decisions can narrow, strengthening both profitability and resilience.

REFERENCES

1. Berger A. N.; Mester L. J. Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions? // Journal of Banking & Finance. — 1997. — Vol. 21. — No. 7. — P. 895–947.
2. Demirgüç-Kunt A.; Huizinga H. Determinants of Commercial Bank Interest Margins and Profitability: Some International Evidence // The World Bank Economic Review. — 1999. — Vol. 13. — No. 2. — P. 379–408.
3. Levine R. Finance and Growth: Theory and Evidence // Aghion P.; Durlauf S. (eds.). Handbook of Economic Growth. — Amsterdam: Elsevier, 2005. — Vol. 1A. — P. 865–934.
4. Saunders A.; Cornett M. M. Financial Institutions Management: A Risk Management Approach. — 9th ed. — New York: McGraw-Hill, 2018. — 768 p.
5. Athanasoglou P. P.; Brissimis S. N.; Delis M. D. Bank-specific, Industry-specific and Macroeconomic Determinants of Bank Profitability // Journal of International Financial Markets, Institutions & Money. — 2008. — Vol. 18. — No. 2. — P. 121–136.
6. Staikouras C.; Wood G. The Determinants of European Bank Profitability // International Business & Economics Research Journal. — 2004. — Vol. 3. — No. 6. — P. 57–68.
7. Wooldridge J. M. Introductory Econometrics: A Modern Approach. — 7th ed. — Boston: Cengage, 2020. — 912 p.
8. Gujarati D. N.; Porter D. C. Basic Econometrics. — 5th ed. — New York: McGraw-Hill, 2009. — 924 p.
9. Flamini V.; McDonald C.; Schumacher L. The Determinants of Commercial Bank Profitability in Sub-Saharan Africa // IMF Working Paper. — 2009. — No. WP/09/15. — 30 p.
10. Bikker J. A.; Vervliet T. Bank Profitability and Risk-taking Under Low Interest Rates // International Journal of Finance & Economics. — 2018. — Vol. 23. — No. 1. — P. 3–18.