Are Banks Near the DEA Efficient Frontier Better-Off?

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Abstract

To assist bankers and bank examiners assess bank performance, a new model is presented that computes a managerial-efficiency frontier of best-practice institutions and determines every banks distance from it. Our research hypothesis is that banks closer to the efficient frontier are significantly different (i.e., better) from those furthest from the frontier when evaluated using various bank performance and risk metrics. We anticipate statistically significant differences between the most-efficient banks and the least-efficient banks for risk-scoping performance ratios that closely align with the CAMELS rating method used by bank examiners.

Our technical model is an input-oriented, constrained-multiplier, data envelopment analysis (DEA) model that evaluates the managerial efficiency of U.S. commercial banks. Using expert opinions from experienced bank examiners, our model uses multiple inputs and multiple outputs with upper- and lower-bounds on the constraint multipliers to compute a scalar measure of efficiency for each bank for each time period.

The model is tested using quarterly data from nearly 8,000 banks for the period 2005-2020. U.S. community banks closest to this efficient frontier are significantly healthier, safer, and sounder according to key metrics and have stronger capital positions, improved liquidity, healthier asset quality, and higher profitability. Moreover, these banks are less likely to become problem banks and fail when evaluated against the adjusted Texas ratio, a banking metric that appraises the general level of problem loan losses against a banks capital buffer.

Our model could have important implications for bankers and bank examiners by helping them better understand what drives managerial efficiency and to identify sources of inefficiency in individual banks. For bank examiners who rely on off-site risk-modeling tools to monitor individual banks—particularly smaller institutions that do not have as frequent on-site examinations—it may be possible to use the results from our model as a proxy for qualitative management assessments.

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1 Introduction and Motivation

Banks play an important role in the U.S. economy. As financial intermediaries, banks can efficiently allocate credit and effectively manage risks that allow the economy to operate at a higher level of activity than it would otherwise (Demirguc-Kunt and Levine [18]). Moreover, a stable, trusted, and healthy financial system is foundational to a nation's economic growth (Beck and Levine [6]; Demirguc-Kunt and Maksimovic [19]; Levine [22]). As far back as 1858, British Prime Minister William Gladstone articulated the importance of financial institutions in generating economic growth when he said: "Finance is, as it were, the stomach of the country, from which all the other organs take their tone." Indeed, well-developed financial markets are essential for an economy to receive the right resources at the right times and in the right places (Siems and Ratner [38]).

Schumpeter [33], perhaps most famous for his ideas on creative destruction and the importance of entrepreneurship, also recognized the importance of financial intermediaries. He argued that they serve as key agents in efficiently allocating funds to business leaders, and that their role in gathering savings, assessing projects, managing risks, monitoring and helping managers, and ensuring that financial transactions are smooth and safe, are essential to innovation, entrepreneurship, and economic growth. His summary view is that financial institutions play an important and direct role in generating higher rates of productivity growth and economic growth.

As a result of banking's important role in a nation's economy, research on bank efficiency has a long and ongoing history. To ensure that a nation's financial system is healthy and productive, it is necessary that its financial institutions function as efficiently as possible. But how should bank efficiency be measured? And how is efficiency related to performance?

A review of the literature indicates that there are many ways to define and measure bank efficiency, including pure technical efficiency, scale efficiency, allocative efficiency, cost efficiency, profit efficiency, scope efficiency, and more (Alber et al. [1]). In this paper, we want to have a holistic measure of bank efficiencywhat we will call managerial efficiencythat captures a bank's strategic focus, execution, and environment.

To do so, we employ Data Envelopment Analysis (DEA), a popular non-parametric, linear-programming-based modeling technique that allows us to take multiple inputs and multiple outputs of different scales and units and turn them into a single scalar measure of efficiency. In essence, our DEA model is intended to capture how well a bank's management takes its limited resources and turns them into high-performing outputs. Moreover, this managerial efficiency metric serves as a benchmark, where each bank is scored relative to all other banks in each time period. In other words, for each point in time where we have data, the most-efficient institutions create an efficiency frontier against which all other institutions can be compared.

Once we calculate the individual bank managerial efficiency scores, our interest is in comparing how groups of banks at different efficiency levels compare to one another on traditional financial indicators that bankers and bank examiners regularly follow to measure bank performance, riskiness, and the likelihood of failure. As our title suggests, our motivation is to answer the question, "Are banks on the DEA efficiency frontier better-off with respect to key banking metrics?" An affirmative answer has implications wherein bankers and bank examiners can potentially use this model to better understand what drives managerial efficiency for banks and to identify sources of inefficiency in individual banks. Furthermore, an affirmative answer suggests that it may be possible to use the managerial efficiency scores from this model in off-site risk-scoping analyses and failure-prediction models as a proxy for qualitative management assessments.

From here on, our paper is organized as follows: Section 2 presents a brief overview of the literature on both DEA and bank efficiency. Section 3 is a technical description of the DEA model that we employ to measure managerial efficiency. In Section 4, we further articulate our hypotheses, and in Section 5 we define the data and the weights used to develop our model. Section 6 presents the results of our analyses and Section 7 concludes with how this study has furthered the bank efficiency literature and provides recommendations for future research.

2 Literature Review on DEA and Bank Efficiency

Since its technical development by Charnes et al. [14], data envelopment analysis (DEA) has been used to measure the relative efficiency of similar decision-making units (DMUs) within a group of firms (or branches or franchises or non-profit organizations) that all operate in a similar domain. Some of the industries where DEA has been utilized the most include banking, health care, agriculture, transportation, education, energy/power, and manufacturing; however, the list of other industry applications is large and growing. Seiford and Thrall [35] and Seiford [34] documented DEA applications and model refinements in the early years of DEA's development. Cook and Seiford [16] published a comprehensive survey of DEA developments through its first 30 years. A few years later, Liu et al. [23] compiled a comprehensive survey of DEA applications, consisting of nearly 5,000 academic papers involving DEA.

Liu et al. also present the main development trajectories for five major DEA application areas: banking, health care, agriculture, transportation, and education. In banking, Sherman and Gold [36] were the first study to use DEA to evaluate the efficiency of bank branches followed by Parkan [27], who performed a similar study in Canada and Rangan et al. [28] who extending DEA to evaluate banks in the banking industry.

This research was followed by three DEA studies examining efficiency changes over time, including Elyasiani and Mehdian [20], who looked at U.S. commercial banks, and Berg et al. [7, 8], who evaluated Norwegian banks. Barr et al. [4] employed DEA to measure managerial efficiency of banks to show that surviving banks are significantly more efficient than banks that are on their way to failure. Barr et al. [5] extended the usefulness of this model by using DEA efficiency scores as a variable in a bank failure-prediction model.

Berger and Humphrey [9] document more than 130 studies of bank efficiency, including those using parametric methods and those using non-parametric methods. Thanassoulis [40] examines the use of DEA in evaluating bank efficiency and suggest its potential usefulness in assessing, monitoring, and improving bank performance. Luo [25] applies DEA to evaluate the efficiency of large banks.

This paper generally follows the approach used in Barr et al. [3], who used DEA to evaluate the productive efficiency of banks from 1984-1998 and found a close relationship between efficiency, financial performance, and soundness as determined by bank examiner ratings. While we do not have access to confidential bank examiner ratings, we can examine the relationship of our managerial efficiency scores against traditional bank performance and risk metrics and the so-called Texas ratio, which assesses the general level of problem loan losses against a bank's capital buffer (Siems [37]).

3 DEA Models to Measure Efficiency and Develop Frontiers

Data envelopment analysis is a mathematical technique for comparing the relative performance of several similar entities, each of which transforms a set of *inputs* into one or more *outputs* through its own (undefined) process. These entities are termed *decision-making units*, or DMUs, indicating that the transformation process involves making decisions about the use of its input resources to create the performance outputs. A DMU can be any system with measurable inputs and outputs, such as a bank, bank branch, airline, hospital, and factory final-assembly process. See Liu et al. [23] for a survey of applications.

DEA's metric for comparing DMUs is based on a generalization of the familiar benefit-cost ratio of outputs generated divided by input resources employed. The inputs and outputs are organized such that an increase in inputs (resources consumed) is expected to yield increased outputs (performance measures), and greater outputs are desirable, as are lower inputs. Consider the simplest case: a set of n DMUs with each DMU k using one input X_k to produce a single output Y_k. The efficiency of each is $E_k = Y_k/X_k$. Hence, the DMUs can be compared using their individual efficiencies, the best being the one with the highest efficiency score.

Data envelopment analysis generalizes this approach by allowing each DMU k to use a set of inputs $I = \{1, \ldots, m\}$ to produce a set of outputs $R = \{1, \ldots, s\}$, such that each known input value is denoted by $X_{ik}, i \in I$, and each output value is $Y_{rk}, r \in R$. By assigning a weight $\overline{v}_i$ to each input i and weight $\overline{u}_r$ to each output r, a *technical efficiency score* E_k can be expressed as the ratio of weighted outputs to weighted inputs:

$$E_k = \frac{\sum_{r \in R} Y_{rk} \overline{u}_r}{\sum_{i \in I} X_{ik} \overline{v}_i}$$

where $\overline{u}_r$ and $\overline{v}_i$ are weights or *multipliers* for an individual output r and input i, respectively. Although this expression can define efficiency, it does not specify what to use. Different weights can change a DMU's efficiency score and different DMUs will prefer different multipliers. Instead of selecting a set of static weights to be applied to all units, DEA separately determines the set of multipliers that maximizes its efficiency, while ensuring that no DMU's efficiency exceeds 1 when thes weights. If a set of weights can be found to produce an efficiency score of 1, that is an efficient DMU; otherwise, the DMU is inefficient because of the dominating performance of one or more other units.

3.1 DEA Model Definitions

While there are many DEA formulations, the original DEA paper by Charnes et al. [14] describes an optimization model for determining the weights and efficiency scores for a set of DMUs under the assumption of *constant returns to scale* (CRS), as discussed below. For each DMU, the weights are optimized to maximize its efficiency, while limiting each DMU's efficiency to 1 when applying the same weights. This model is defined as follows for assessing the efficiency of DMU_o.

$$\begin{aligned}
E_o &= \max \frac{\sum_{r \in R} Y_{ro} \overline{u}}{\sum_{i \in I} X_{io} \overline{v}} \\
\text{subject to:} & \\
E_k &\leq 1, \text{ for all } k \in K \\
\overline{u}_r, \overline{v}_i &\geq \varepsilon, \text{ for all } r \in R, i \in I
\end{aligned}$$

where ε is a small, positive, non-archimedian value. This fractional-programming problem can be converted into an equivalent linear programming problem with transformed variables $v_i, i \in I$, and $u_r, r \in R$, to maximize weighted outputs or minimize weighted inputs. An example of an output-oriented version of this CRS model is shown as:.

$$\begin{aligned}
CRS_i: \quad & E_o = \max \sum_{r \in R} Y_{ro} \overline{u}_r \\
\text{subject to:} \quad & \sum_{i \in I} X_{io} \overline{v} = 1 \\
& \sum_{r \in R} Y_{ro} \overline{u}_r - \sum_{i \in I} X_{io} \overline{v}_i \leq 0, \text{ for all } k \in K \\
& \overline{u}_r, \overline{v}_i \geq \varepsilon, \text{ for all } r \in R, i \in I
\end{aligned}$$

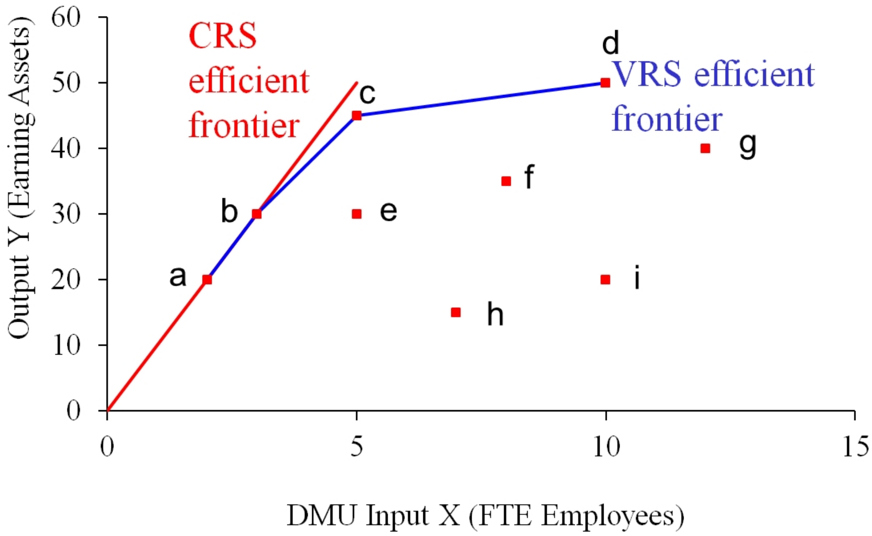

Figure 1: DMUs with CRS and VRS efficient frontiers

If the solution of CRS_i for DMU$_o$ results in an efficiency score $E_o = 1$, it is efficient relative to the other DMUs; otherwise, it is inefficient because others are more productive. After solving this model for every DMU, those with an efficiency of 1 form the population's *efficient frontier* of best performance.

The CRS assumption assumes that outputs increase with increased inputs at the same rate irrespective of the input scale. However, in many situations efficiency rates can vary with the scale or size of the inputs. Banker et al. [2] extend the CRS model to allow for *variable returns to scale* (VRS) in defining the efficiency of DMUs. A VRS version of the above DEA model is as follows.

$$
\begin{aligned}
VRS_i: \quad & E_o = \max \sum_{r \in R} Y_{ro}\overline{u}_r - v_o \\
\text{subject to:} \quad & \sum_{i \in I} X_{io}\overline{v}_i = 1 \\
& \sum_{r \in R} Y_{ro}\overline{u}_r - \sum_{i \in I} X_{io}\overline{v}_i - v_o \leq 0, \text{ for all } k \in K \\
& \overline{u}_r, \overline{v}_i \geq \varepsilon, \text{ for all } r \in R, i \in I \\
& v_o \quad \text{unrestricted in sign}
\end{aligned}
$$

The difference between the two approaches is illustrated in Figure 1 where DMUs $a - g$ have a single input X of full-time-equivalent number of employees and a single output Y of earning assets displayed as a scatter plot.

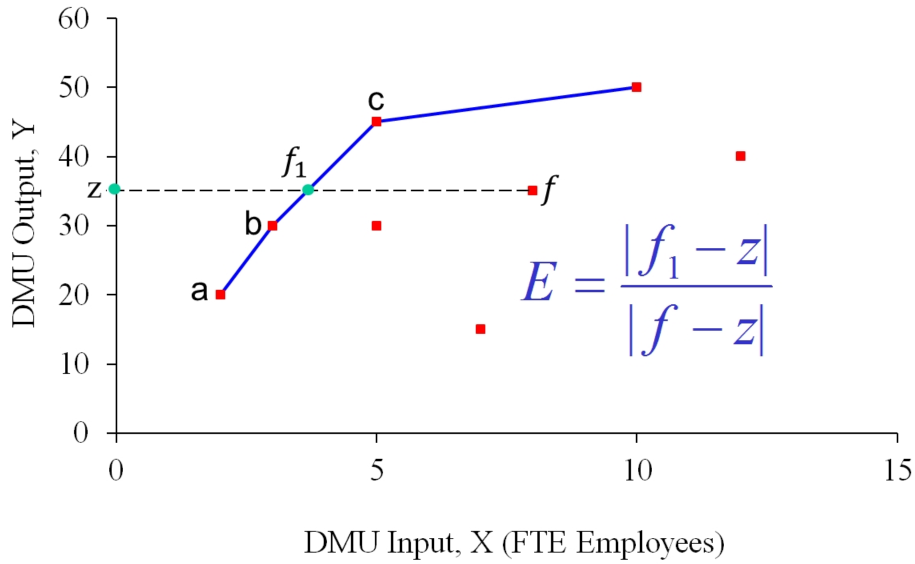

Figure 2: Assessment of Input Efficiency for DMU f Relative to VRS Frontier

The CRS_i efficient frontier is shown as a red line that includes DMUs a and b only, with the remaining units $c - g$ being inefficient relative to a and b. The VRS_i model results in an efficient frontier indicated as blue lines that connect the best-performing units a, b, c, and d. By allowing the efficiency-ratio definition to vary with the scale or size of the input, additional DMUs reflect best performance relative to other units with similar inputs, not necessarily relative to all DMUs.

The efficiency score E measures relative transformational efficiency by determining each DMU's distance from the efficient frontier. When viewing this distance from an input orientation, it can represent a right-sizing factor for inefficient units. For example, in Figure 2, DMU f with (u, v)=(8,35) would need to reduce its input until it reached point f_1 at (3.67,35)to be as efficient as DMUs b and c. Its efficiency score would be the distance from f_1 to point z (with no input) divided by the distance from f to z, giving $E_f = 3.67/8 = 0.458$. To become as efficient as DMUs b and c, unit f's input should be reduced to 45.8% of its current value. For a practical application, perhaps f's management should seek guidance from b and c about how it could improve its operation.

The use of DEA for performance assessment differs greatly from multivariate statistical methods, such as regression. Regression models are based on a single output measure (the dependent variable), assume normally distributed data, and are focused on central tendency analysis, making difficult the identification of best practice. In contrast, DEA is an extremal method that allows multiple input and output factors and determines an efficient frontier of top-performing units against which inefficient DMUs are benchmarked. Each inefficient unit is provided an estimate of its distance from the frontier, realistic goals for achieving best practice, suggestions for benchmarking partners, and an integrative and interpretive framework to assess their situation and suggest improvement areas.

3.2 Including Expert Judgement in Models via Weight Restrictions

When giving multiple-input, multiple-output models complete freedom in setting weights, unexpected and inappropriate results can result. Factors of minor importance can be over-emphasized and key elements may be assigned zero weights in order to maximize the efficiency score of a given DMU. To ensure that realistic multipliers are used for efficiency calculations, weight restrictions can be added to a model's constraint set.

Since predetermined weight limits are difficult to assess, Charnes, et al. [13] developed their "cone-ratio" method for specifying restrictions as polyhedral convex cones wherein relationships between variables and groups of variables can be represented as linear constraints. This enables, for example, (a) ensuring that a given input's weight is at least 10%, but no more than 40%, of the sum of all input weights, (b) the weight on output 1 cannot be greater than that of a more-important output 2, or (c) the sum of the weights for input group A must be larger than those for group B. See Cook and Seiford [16], for a summary of weight restriction approaches.

Such restrictions are typically assessed by experts in the area of application, since they can significantly influence the model's results. In this paper, we relied on the expert judgments of twelve experienced bank examiners, as described in Section 5.

4 Hypotheses

Our main hypothesis is that banks closer to the DEA efficiency frontier are significantly different (i.e., better) from those furthest from the frontier when evaluated using various bank performance and risk metrics. We expect to see statistically significant differences between the most-efficient banks and the least-efficient banks for risk-scoping performance ratios that closely align with the CAMELS rating method used by bank examiners. That is, banks closer to the managerial efficiency frontier should have better capital and liquidity positions, higher profitability, fewer problem assets, and be less likely to fail.

The CAMELS ratings framework was originally developed in 1979 by the regulatory agencies with the goal of capturing the safety and soundness of an individual bank.[1] CAMELS is an acronym that addresses the following six

[1]The Federal Financial Institutions Examination Council (FFIEC) adopted the Uniform Financial Institutions Rating System (UFIRS) as an effective internal supervisory tool for evaluating the safety and soundness of banks. Originally known as the CAMEL rating with five components, the framework was modified in 1997 to CAMELS with six components. See

components:

- **C**apital Adequacy
- **A**sset Quality
- **M**anagement Quality
- **E**arnings Ability
- **L**iquidity
- **S**ensitivity to Market Risk

Each of the components is assigned a rating from 1 to 5, with 1 being the strongest rating (Stackhouse [39]). A composite CAMELS rating from 1 to 5 is also assigned after a careful evaluation of an institution's managerial, operational, financial, and compliance performance. A composite rating of 1 indicates solid performance and risk management practices relative to the institution's size, complexity, and risk profile. A 5 rating indicates a critically deficient level of performance and inadequate risk management practices and is cause for the greatest supervisory concern.

Within these components, bank examiners often rely on off-site monitoring tools to assess a bank's condition. Most of the ratios used in these tools can be categorized under one of the six CAMELS components. For example, Manthoulis et al. [26] present a bank failure prediction model using the seven financial indicators shown in Table 1. These ratios are widely accepted by financial institution regulators around the world for assessing the strength and health of individual banks (Lopez [24]; Sahajwala and van den Bergh [32]; The World Bank and The International Monetary Fund [42]) and have been used extensively in academic research for understanding bank performance and for predicting bank failure (Cole and White [15]; Zopounidis et al. [44]; Zhao et al. [43]).

We will use these financial indicators along with a few additional metrics, as well as the adjusted Texas ratio to evaluate the differences in banks closest to the DEA efficiency frontier from those furthest away. In essence, the adjusted Texas ratio examines a bank's nonperforming assets with respect to its tangible capital and loan loss provision. In other words, the ratio measures the potential credit problems at a bank. When a bank's adjusted Texas ratio exceeds 100%, it is far more likely to fail because its nonperforming assets exceed the bank's resources needed to absorb potential losses on those assets.

In light of the CAMELS components, our hypotheses is that banks closest to the DEA managerial efficiency frontier should have better capital (equity) positions, fewer problem assets and lower concentrations in riskier loan markets, like construction and development lending and commercial and industrial loans, higher return on assets and wider net interest margins, stronger liquidity positions, less sensitivity to market risk, and a lower likelihood of failure as measured by the adjusted Texas ratio.

FDIC Law, Regulations, Related Acts - Statements of Policy.

Table 1: Financial Indicators in Manthoulis et al. (2020) Bank Failure Prediction Model

CAMELS Component	**Financial Indicator**
Capital Adequacy	Equity/Total Assets
Asset Quality	Loan Loss Allowances/Total Loans
Management Ability	Expenses/Revenues
Earnings Ability	Net Income/Total Assets
Earnings Ability	Net Interest Margin
Liquidity	Total Loans/Total Deposits
Sensitivity to Market Risk	(Off-Balance Sheet Risk - Weighted Assets) / (Total Risk-Weighted Assets)

5 Data and Model Parameters

We utilize quarterly bank Call Report data from the Federal Financial Institutions Examination Council (FFIEC) for the period from the third quarter of 2005 to the fourth quarter of 2020. The total number of banks in our study was nearly 8,000 at the beginning of our period of analyses and close to 5,000 at the end, although the number changed from quarter-to-quarter because of mergers/acquisitions and ongoing consolidation.

The FFIEC is a formal interagency body empowered to prescribe uniform principles, standards, and report forms for the examination of financial institutions. On their website, the FFIEC maintains the Uniform Bank Performance Report (UBPR): an analytical tool created for bank supervisory, examination, and management purposes. All variables and ratios used in this analysis were derived from these data.

As described in Section 3, DEA incorporates multiple input and output variables of potentially different scales and units into a single measure of efficiency from 0 (extremely inefficient) to 1 (optimally efficient). In our model, each bank is considered as a decision-making unit (DMU) with the goal of maximizing its own DEA efficiency score subject to all other banks during each quarter as constraints in the model. As described above, the constrained-multiplier model requires that the weights (u_r, v_i) be within some predefined range.

To determine the best input and output variables to use in our model, and to determine the best upper and lower bounds on each input and output variable, we surveyed twelve experienced bank examiners from across the nation. Our goal is two-fold: first, to select the best variables that bank management has some control over in efficiently converting inputs (resources) into high-performing outputs. And second, to prescribe weights for each input and output variable that identifies the most impactful variables and gives them potentially higher weights than variables that are considered as less impactful/meaningful in our model.

Table 2: DEA Model Variables and Constraints for the Multipliers (Weights)

Input Variables	Lower Bound	Average Bound	Upper Bound
Number of Full Time Equivalent Employees	2.8%	8.6%	46.5%
Number of Branch Offices	2.0%	5.0%	14.0%
Non-Interest Expenses	5.2%	22.5%	43.5%
Interest Expenses	6.0%	11.9%	20.1%
Purchased Funds	3.3%	7.4%	18.2%
90+ Days Past Due Loans and Leases Accruing Interest	3.4%	28.3%	48.9%
Total Loans and Leases in Nonaccrual	2.9%	16.4%	37.1%
Output Variables	**Lower Bound**	**Average Bound**	**Upper Bound**
Earning Assets	6.2%	20.1%	39.5%
Interest Income	7.9%	22.1%	39.5%
Non-Interest Income	4.5%	11.9%	28.8%
Provision for Loan and Lease Losses	4.8%	46.0%	72.1%

We start with a slate of input and output variables that capture the essential financial intermediation functions of a bank and that have been employed in similar studies in the past (Berger and Mester [10]; Guarda et al. [21]). Again, our goal is to have a holistic measure of managerial efficiency that accurately describes a bank's strategic focus, execution, and environment. Thus, we use variables that management has some decision-making control over in operating its institution, such as how many employees to hire, how many branch offices to manage, how best to gather and pay for deposits, how to handle loans that do not perform according to expectations, and how to generate income and earning assets.

We then verified the importance of these variables with our group of twelve experienced bank examiners and aggregated their responses using the analytic hierarchy process, or AHP (Saaty [29, 30, 31]; Bernasconi et al. [11]). AHP helps us establish priority weights for each set of input variables and each set of output variables. Table 2 shows the input and output variables used in our DEA model, the average weight computed from the examiner surveys, and the upper and lower bound constraints for the multipliers (weights).

Most DEA models are sensitive with respect to the selection of the input and output variables, as well as the weights used to constrain the multipliers. We found that the range delineated by the upper and lower bounds as constraints on the respective multipliers for each variable gave us the best distribution of DEA efficiency scores.

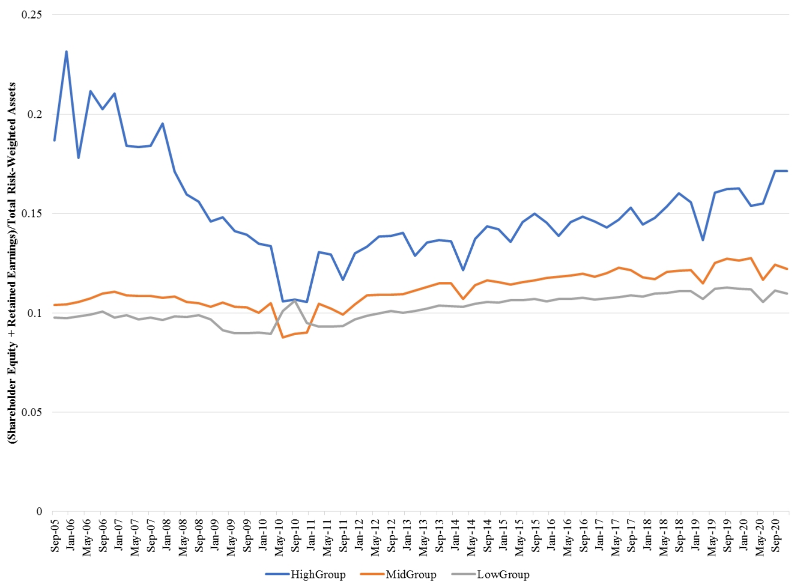

Figure 3: Tier 1 Capital Ratio

6 Results

We ran our DEA model for each time period and separated the banks into three cohorts: high-efficiency banks had DEA managerial efficiency scores of 0.7 to 1.0; mid-efficiency banks had scores between 0.3 and 0.7; and low-efficiency banks had scores below 0.3. Over time, the makeup of banks and the number of banks in each cohort changed as the DEA model was run one period at a time.

The results of our hypothesis tests are organized below using the CAMELS rating framework. We test for statistical differences between the highest-efficiency cohort and the lowest-efficiency cohort using a standard z-test of means. For each performance/risk metric, we include a time-series chart of the three cohorts and summarize the statistical differences in a table that shows the z-statistic value and its level of significance (*** = 0.01 level of significance; ** = 0.05 level of significance; * = 0.10 level of significance).

6.1 Capital Adequacy

To measure capital adequacy, we use the Tier 1 capital ratio. This ratio is an excellent gauge of a bank's financial health as it measures a bank's core capital relative to its total risk-weighted assets. Higher capital positions provide greater assurance against unexpected losses.

As shown in Figure 3, over time, the banks in our most-efficient cohort had more Tier 1 capital as a percentage of total risk-weighted assets than the other

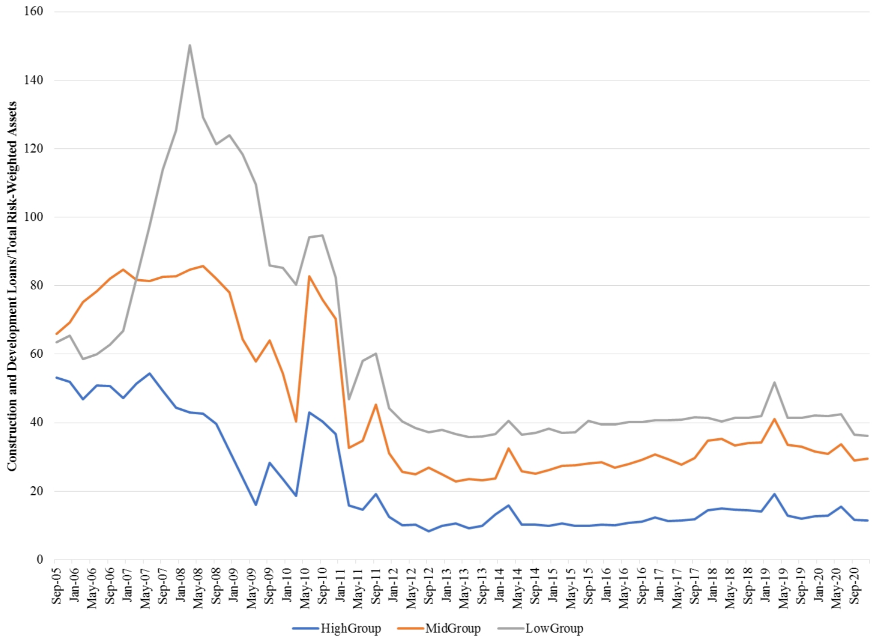

Figure 4: Construction and Development Loan Concentration

two cohorts. Moreover, when the high-efficiency group is compared with the low efficiency group, significant statistical differences are detected in 61 of the 62 quarters, and were highly significant in 60 quarters (see Table 3).

6.2 Asset Quality

To evaluate asset quality, we examine three metrics: two that examine loan concentrations in traditionally riskier activities and one that examines the level of loans past due 90+ days plus those in nonaccrual status. Figure 4 shows the level of construction and development loans as a percentage of risk-weighted assets for the three cohorts. The group of banks with the highest efficiency have the lowest concentration of construction and development loans. And, as shown in Table 3, there are statistically significant differences between the highest-efficiency banks and the lowest-efficiency banks for 52 of the 62 quarters.

A similar story can be told for the concentration of commercial and industrial (C&I) loans. As shown in Figure 5, the high-efficiency banks generally have lower C&I loan concentrations, and as shown in Table 3, the difference between the high-efficiency banks and the low-efficiency banks is statistically significant in 56 of 62 quarters.

The last asset quality metric we examined was the level of loans past due 90+ days plus those in nonaccrual status, all relative to total loans. As shown

Table 3: Capital and Asset Quality: High- Versus Low-Efficiency Banks, Differences in Means z-Test

	Capital Adequacy		**Asset Quality**					
	Tier One Capital Ratio		**Constr. & Dev. Loans/ Total Risk Based**		**Comm. & Ind. Loans/ Total Risk Based**		**Past Due Loans & Nonacc./**	
Date	z-statistic	significance level	z-statistic	significance level	z-statistic	significance level	z-statistic	significance level
Sep-05	3.5964	***	-0.6548		-2.4609	**	-43.3855	***
Dec-05	2.3427	**	-0.9354		-2.3693	**	-40.2892	***
Mar-06	13.0350	***	-1.3435		-3.8871	***	-41.6985	***
Jun-06	7.0142	***	-1.2638		-4.6364	***	-37.3064	***
Sep-06	10.7783	***	-1.8670	*	-5.9542	***	-33.3331	***
Dec-06	9.0101	***	-3.6273	***	-5.9729	***	-26.8820	***
Mar-07	13.2532	***	-2.0788	**	-3.3165	***	-47.9526	***
Jun-07	11.1821	***	-2.8320	***	-3.7100	***	-34.2983	***
Sep-07	12.5816	***	-3.3196	***	-3.4322	***	-36.6348	***
Dec-07	7.6682	***	-4.2952	***	-3.3553	***	-31.3015	***
Mar-08	12.9382	***	-2.1957	**	-1.6521	*	-32.3342	***
Jun-08	14.1786	***	-1.6356		-1.4125		-27.6259	***
Sep-08	14.2363	***	-3.0209	***	-2.0015	**	-29.4841	***
Dec-08	14.1482	***	-3.8897	***	-2.1752	**	-31.5781	***
Mar-09	15.9493	***	-9.9235	***	-6.4726	***	-25.1784	***
Jun-09	15.9051	***	-4.5990	***	-4.8448	***	-22.6646	***
Sep-09	17.0075	***	-0.4949		-4.1989	***	-20.3983	***
Dec-09	15.3885	***	-10.1940	***	-5.3854	***	-15.0081	***
Mar-10	14.8402	***	-13.7509	***	-7.0657	***	-16.6956	***
Jun-10	5.6890	***	-0.2187		0.1440		-1.0974	
Sep-10	0.7667		-0.1534		0.3665		-1.0424	
Dec-10	13.6961	***	-0.3031		0.4623		-1.8103	*
Mar-11	12.0994	***	-0.3969		-4.0534	***	-17.9134	***
Jun-11	13.1732	***	-15.5164	***	-4.0966	***	-20.7192	***
Sep-11	18.0404	***	-3.6511	***	-1.1736		-18.6658	***
Dec-11	9.9106	***	-20.6114	***	-2.8059	***	-11.6796	***
Mar-12	9.9386	***	-20.0781	***	-4.7341	***	-14.0758	***
Jun-12	9.7625	***	-26.9601	***	-4.4041	***	-12.0572	***
Sep-12	9.7787	***	-7.8127	***	-3.8989	***	-7.2566	***
Dec-12	9.2314	***	-26.3179	***	-4.9795	***	-9.3654	***
Mar-13	7.9685	***	-21.8571	***	-5.3438	***	-10.5316	***
Jun-13	8.0709	***	-27.4728	***	-5.2608	***	-11.7856	***
Sep-13	8.0873	***	-26.0931	***	-5.2340	***	-10.4514	***
Dec-13	6.9920	***	-8.9447	***	-4.4949	***	-7.9721	***
Mar-14	10.3675	***	-13.7876	***	-3.6347	***	-10.2722	***
Jun-14	7.9813	***	-22.5363	***	-5.1135	***	-7.0835	***
Sep-14	8.1150	***	-22.8903	***	-6.6328	***	-3.5239	***
Dec-14	7.7218	***	-26.9622	***	-6.7285	***	-7.2782	***
Mar-15	7.0137	***	-20.6758	***	-4.5486	***	-4.2178	***
Jun-15	7.4316	***	-24.0800	***	-4.3332	***	-2.7530	***
Sep-15	7.6757	***	-5.2455	***	-1.3637		-4.4667	***
Dec-15	7.7933	***	-25.8647	***	-5.0954	***	-3.6782	***
Mar-16	7.2539	***	-26.0757	***	-5.6769	***	-1.5414	
Jun-16	7.4323	***	-25.0650	***	-6.0804	***	-1.7599	*
Sep-16	7.5852	***	-24.2156	***	-5.3973	***	-0.9233	
Dec-16	7.6079	***	-19.7917	***	-4.1813	***	-0.4482	
Mar-17	7.6343	***	-23.2487	***	-6.6998	***	-0.7523	
Jun-17	7.3443	***	-23.2453	***	-7.4924	***	-2.1947	**
Sep-17	7.9398	***	-21.5716	***	-5.7259	***	-2.6253	***
Dec-17	7.8403	***	-17.5762	***	-3.4836	***	-5.9735	***
Mar-18	7.8271	***	-14.8108	***	-3.5623	***	-8.0650	***
Jun-18	8.0599	***	-15.5613	***	-3.7885	***	-5.6729	***
Sep-18	8.7966	***	-17.0096	***	-4.3419	***	-3.0765	***
Dec-18	8.2222	***	-18.1666	***	-4.1250	***	-3.7828	***
Mar-19	14.7269	***	-10.8548	***	-3.6561	***	2.6339	***
Jun-19	8.3186	***	-19.0529	***	-5.9570	***	-3.7643	***
Sep-19	8.3681	***	-21.2841	***	-6.2368	***	-4.4374	***
Dec-19	7.4131	***	-20.5859	***	-5.5389	***	-2.7776	***
Mar-20	8.0046	***	-19.5328	***	-5.6021	***	-1.8486	*
Jun-20	9.5153	***	-16.3174	***	-4.4942	***	-1.5390	
Sep-20	5.2224	***	-14.6073	***	-5.6899	***	-5.6923	***
Dec-20	5.5329	***	-13.7718	***	-6.1371	***	-7.3143	***

***	60	***	49	***	51	***	51
**	1	**	2	**	4	**	1
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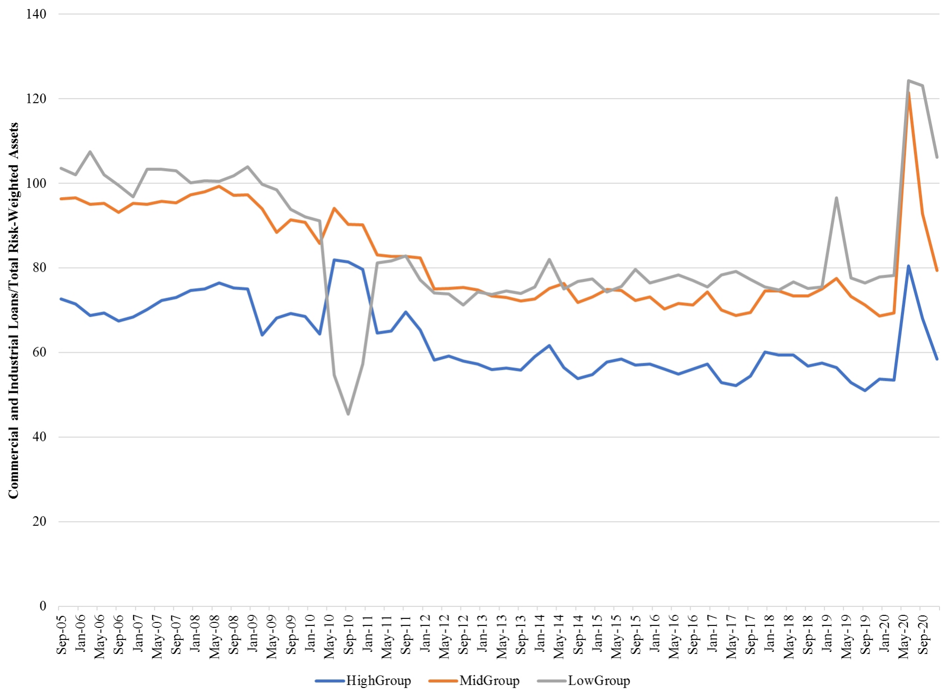

Figure 5: Commercial and Industrial Loan Concentration

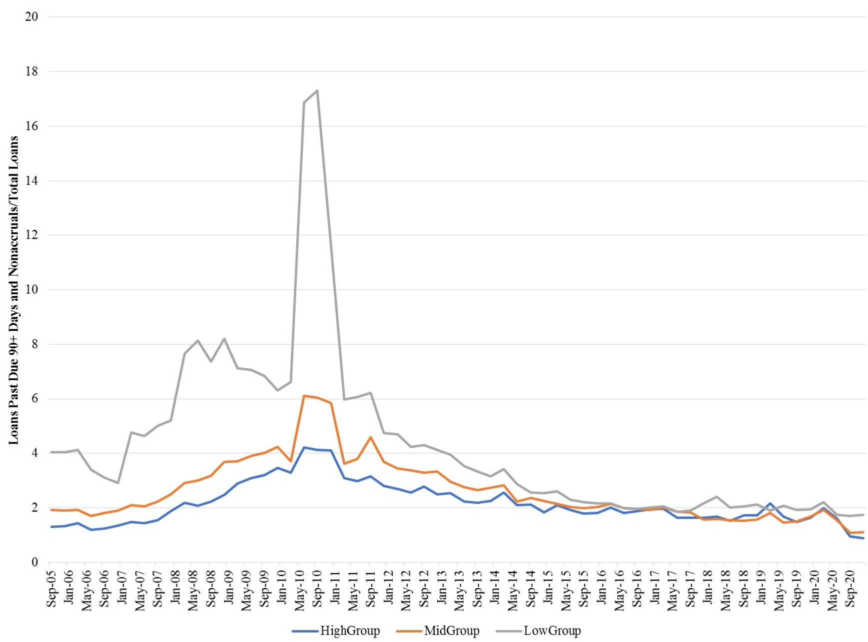

Figure 6: Problem Loans

in Figure 6, problem loans were more of an issue for the low-efficiency banks, particularly before and during the 2008-09 financial crisis. Yet, even though the differences are smaller in the more-recent periods, many are still statistically significant. And overall, 55 of the 62 quarters showed statistically significant differences between the high-efficiency banks and the low-efficiency banks.

6.3 Earnings

To evaluate possible earnings differences between the highest-efficiency banks and the lowest-efficiency banks, we examine a number of income and expense ratios that should all inform about the best-known earnings metric: return on assets. Figure 7 shows interest income as a percentage of average assets and Figure 8 shows non-interest income as a percentage of average assets. Interestingly, interest income as a percent of average assets is generally lower for the high-efficient banks. Perhaps this is due to taking less risk (as evidenced by the asset quality metrics) and/or from not putting as much capital to work (as shown by the Tier 1 capital ratio). In any case, as shown in Figure 8, the high-efficiency banks tend to have found ways to earn higher levels of non-interest income (except during the most recent two quarters and during the 2008-09 financial crisis), which likely helped them weather this time period of extremely low interest rates. Statistically significant difference levels between

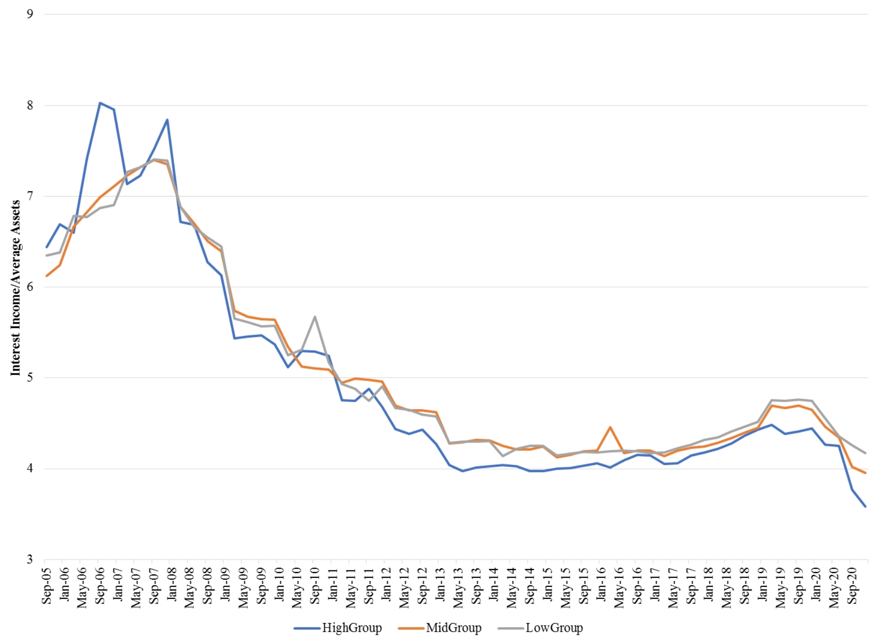

Figure 7: Interest income

the high-efficiency banks and the low-efficiency banks are shown in Table 4.

On the expense side, Figure 9 shows interest expenses as a percentage of average assets and Figure 10 shows non-interest expenses as a percentage of average assets. The high-efficiency banks generally have lower interest expenses and higher non-interest expenses, although the statistical differences between the groups are more significant for interest expenses (Table 4).

Figure 11 shows that for a bank's net interest margin, or the difference between their interest income and their interest expenses, there is surprisingly little difference between the most-efficient banks and the least-efficient banks. However, Figure 12 shows that for the return on average assets metric, high-efficiency banks are generally more profitable than low-efficiency banks, with the exception of the period leading up to, and during, the 2008-09 financial crisis, and for the end of 2020.

6.4 Liquidity

We evaluate three different liquidity metrics to examine potential differences between high- and low-efficiency banks. Figure 13 shows the liquidity ratio, which is simply a bank's current (short-term) assets divided by its current liabilities. And Table 5 shows that there are statistically significant differences in mean values between the high-efficiency banks and the low-efficiency banks.

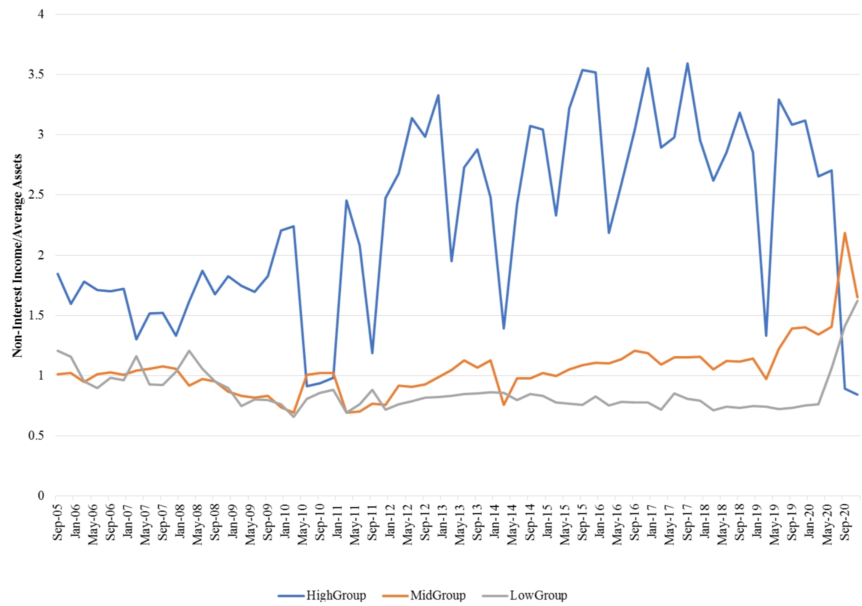

Figure 8: Non-Interest income

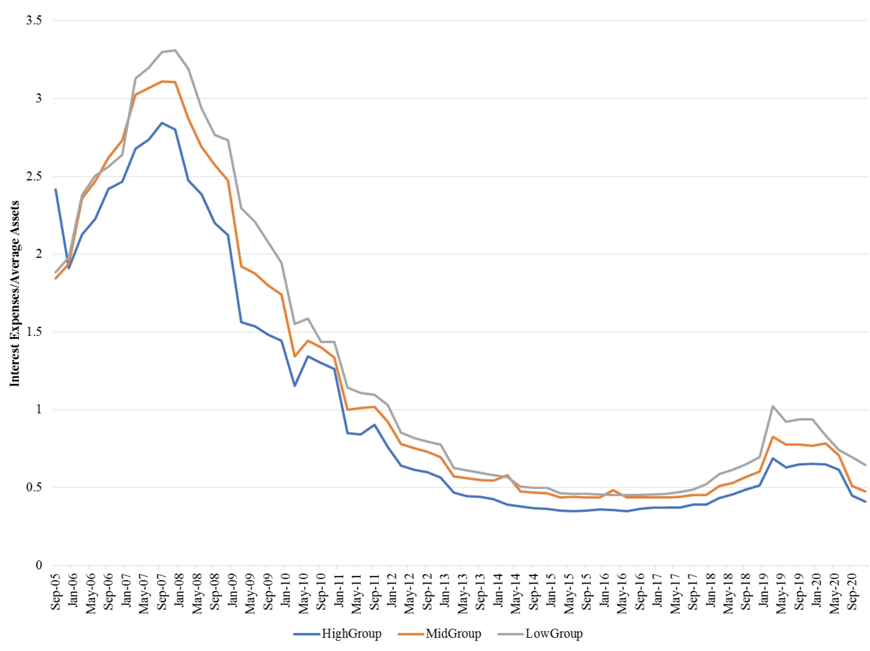

Figure 9: Interest expense

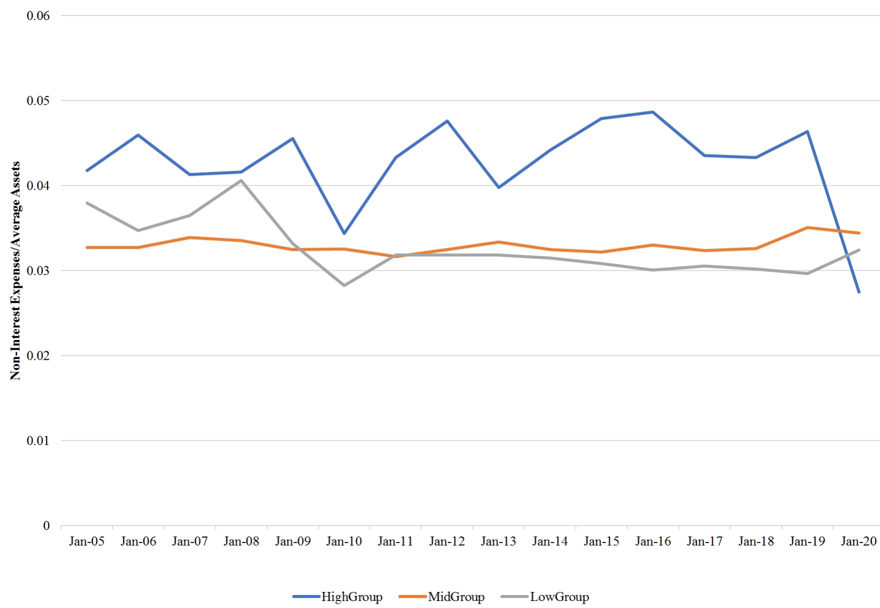

Figure 10: Non-Interest Expenses

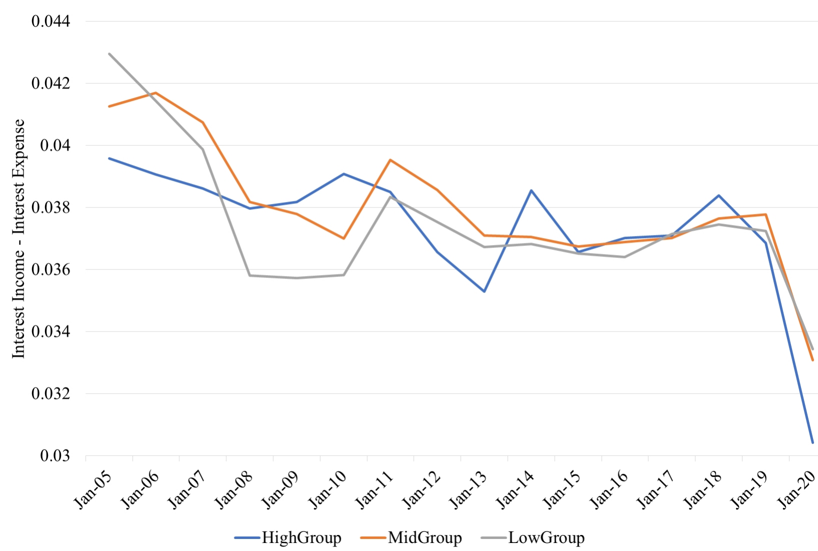

Figure 11: Net Interest Margin

Table 4: Earnings: High- Versus Low-Efficiency Banks, Differences in Means z-Test

	Earnings Ability											
	Interest Income/ Average Assets		Non-Interest Income/ Average Assets		Interest Expense/ Average Assets		Non-Interest Expense/ Average Assets		Net Interest Margin		Return on Average Assets	
Date	z-statistic	significance level	z-statistic	significance level	z-statistic	significance level	z-statistic	significance level	z-statistic	significance level	z-statistic	significance level
Sep-05	0.4014		1.85075	*	0.6744		1.0419		-6.0081	***	-0.6338	
Dec-05	1.0972		1.71514	*	-0.4810		1.2779		-7.1509	***	-1.6232	
Mar-06	-2.1294	**	2.81012	***	-6.5144	***	1.7818	*	-3.1168	***	-0.7466	
Jun-06	1.3228		2.47374	**	-6.0909	***	3.5971	***	0.3772		-3.4094	***
Sep-06	1.7881	*	2.12334	**	-1.6570	*	3.3442	***	-1.4002		-4.6101	***
Dec-06	2.2198	**	2.21464	**	-2.8930	***	3.7104	***	-3.9290	***	-5.2561	***
Mar-07	-1.4465		0.57486		-17.8158	***	1.0218		0.3393		-1.5486	
Jun-07	-1.2212		2.13854	**	-19.6123	***	2.7528	***	-0.8790		-2.0865	**
Sep-07	0.7400		2.18106	**	-8.1074	***	2.6974	***	-1.0728		-1.8138	*
Dec-07	1.3866		1.25327		-11.3558	***	2.2989	**	-2.0788	**	-3.5157	***
Mar-08	-1.1088		1.14050		-28.3622	***	1.0025		6.5947	***	0.5091	
Jun-08	0.0733		1.35233		-11.3844	***	-0.2593		4.1061	***	8.0764	***
Sep-08	-5.9321	***	1.69615	*	-28.0773	***	0.2138		1.9815	**	7.0846	***
Dec-08	-6.5452	***	2.24034	**	-26.2384	***	0.2931		4.3668	***	12.8412	***
Mar-09	-4.4025	***	2.21080	**	-31.8409	***	1.6015		10.9190	***	3.9536	***
Jun-09	-3.1472	***	2.19455	**	-29.0905	***	1.9071	*	9.1027	***	2.9824	***
Sep-09	-1.9022	*	2.35668	**	-30.1249	***	2.3373	**	9.2995	***	2.9231	***
Dec-09	-3.9877	***	3.13994	***	-22.9565	***	3.0915	***	4.6107	***	2.3607	**
Mar-10	-2.0664	**	2.85121	***	-21.0082	***	2.3967	**	4.4575	***	1.9978	**
Jun-10	-0.1054		0.97260		-5.2791	***	7.4989	***	22.5488	***	9.5816	***
Sep-10	-1.2914		0.71167		-2.4525	**	3.1280	***	-13.2436	***	2.5880	***
Dec-10	0.8348		0.90533		-7.5774	***	6.4310	***	20.1145	***	2.7349	***
Mar-11	-2.4420	**	3.47443	***	-20.1805	***	2.5751	**	1.7480	*	3.2347	***
Jun-11	-2.2040	**	3.04140	***	-21.5717	***	1.9245	*	2.1088	**	6.8419	***
Sep-11	4.5857	***	1.68057	*	-24.3646	***	1.4603		11.0337	***	9.7693	***
Dec-11	-3.2183	***	3.29561	***	-20.6717	***	2.5782	***	0.2225		4.0820	***
Mar-12	-3.1819	***	3.79912	***	-17.3222	***	2.8893	***	-0.0016		3.3211	***
Jun-12	-3.5457	***	3.93600	***	-16.8996	***	3.1302	***	-0.7240		4.1594	***
Sep-12	-2.2303	**	3.76570	***	-17.4097	***	3.0884	***	0.2772		3.5540	***
Dec-12	-4.2381	***	3.90823	***	-18.3110	***	3.0557	***	-1.2925		4.3549	***
Mar-13	-3.2340	***	2.46407	**	-15.5726	***	1.4497		-1.2509		2.0260	**
Jun-13	-4.0990	***	3.04883	***	-16.0037	***	2.1446	**	-2.0398	**	3.2083	***
Sep-13	-3.6289	***	3.14758	***	-15.2509	***	2.2612	**	0.9135		3.3810	***
Dec-13	-3.5634	***	2.78253	***	-15.8582	***	1.8982	*	-1.9754	**	2.5278	**
Mar-14	-2.8378	***	2.26497	**	-32.5575	***	2.2389	**	2.2998	**	1.6652	*
Jun-14	-2.2844	**	3.10689	***	-13.0224	***	2.0214	**	-0.6477		3.0149	***
Sep-14	-3.3872	***	3.12705	***	-13.7159	***	2.3496	**	-1.7301	*	2.5636	**
Dec-14	-3.3582	***	3.13464	***	-14.5936	***	2.4466	**	0.5738		2.6442	***
Mar-15	-1.6195		2.92203	***	-11.9362	***	1.8737	*	-0.4354		2.6845	***
Jun-15	-1.7008	*	3.55271	***	-11.7264	***	2.7212	***	-0.2261		2.9412	***
Sep-15	-1.6561	*	3.46803	***	-11.0995	***	2.8762	***	-0.2799		2.9671	***
Dec-15	-1.3469		3.36261	***	-9.6858	***	2.8142	***	0.0616		2.7162	***
Mar-16	-2.1239	**	2.71779	***	-9.6923	***	1.9066	*	-1.0418		1.8812	*
Jun-16	-1.1161		3.00321	***	-10.1985	***	2.3124	**	0.1240		2.1154	**
Sep-16	-0.3834		3.20133	***	-8.1843	***	2.6703	***	0.9009		2.3966	**
Dec-16	-0.3351		3.37701	***	-8.1654	***	2.9181	***	0.7289		2.3092	**
Mar-17	-1.3342		2.77875	***	-8.3519	***	2.2280	**	-0.3573		1.7972	*
Jun-17	-1.9005	*	2.43083	**	-8.8786	***	1.9111	*	-0.6508		1.6864	*
Sep-17	-1.3134		3.03108	***	-8.4787	***	2.5228	**	-0.2077		2.3837	**
Dec-17	-1.6187		2.84154	***	-12.2051	***	2.2187	**	-0.0684		2.6299	***
Mar-18	-1.5148		2.77096	***	-12.1382	***	2.1085	**	-0.0795		2.3285	**
Jun-18	-1.4943		2.83158	***	-11.4953	***	2.2065	**	0.3547		2.6613	***
Sep-18	-1.1138		3.12173	***	-11.1458	***	2.5988	***	0.9846		2.6796	***
Dec-18	-0.9707		2.95992	***	-11.8739	***	2.4805	**	1.1447		2.5697	**
Mar-19	-8.4864	***	2.31217	**	-32.2827	***	2.4639	**	2.1271	**	2.3743	**
Jun-19	-5.4853	***	3.08464	***	-16.1524	***	2.6537	***	-1.2269		2.8218	***
Sep-19	-5.1044	***	2.91905	***	-15.3011	***	2.5995	***	-1.2087		2.4181	**
Dec-19	-4.0967	***	2.90390	***	-14.9134	***	2.6491	***	-0.5251		2.1451	**
Mar-20	-3.7109	***	2.50533	**	-10.2031	***	2.0021	**	-1.4969		2.6372	***
Jun-20	-1.5489		1.64852	*	-8.1244	***	1.4941		0.9943		1.1528	
Sep-20	-6.4305	***	-1.95285	*	-12.0836	***	-3.0605	***	-2.3369	**	-1.3553	
Dec-20	-8.7409	***	-2.71135	***	-13.3013	***	-3.5591	***	-4.6074	***	-3.0571	***
	***	24	***	35	***	58	***	25	***	17	***	35
	**	8	**	14	**	1	**	19	**	8	**	15
	*	5	*	6	*	1	*	7	*	2	*	5
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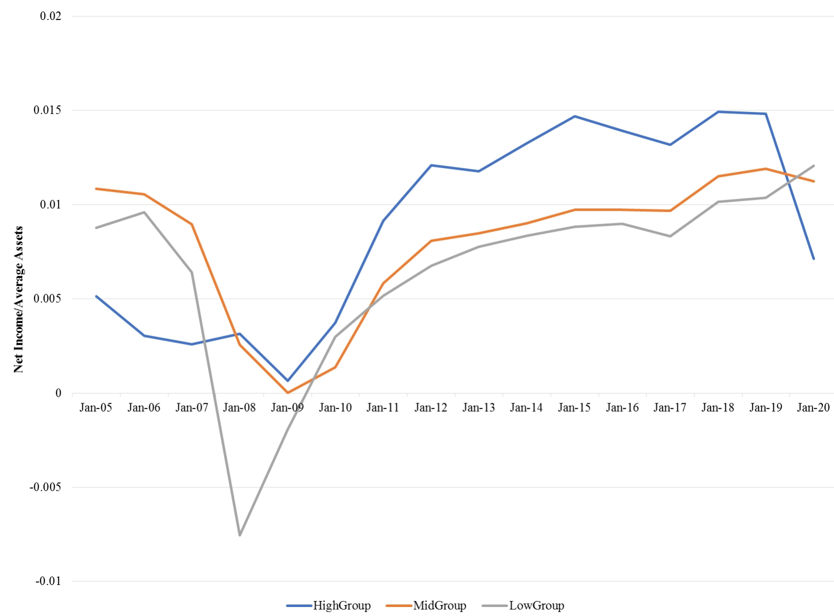

Figure 12: Return on Average Assets

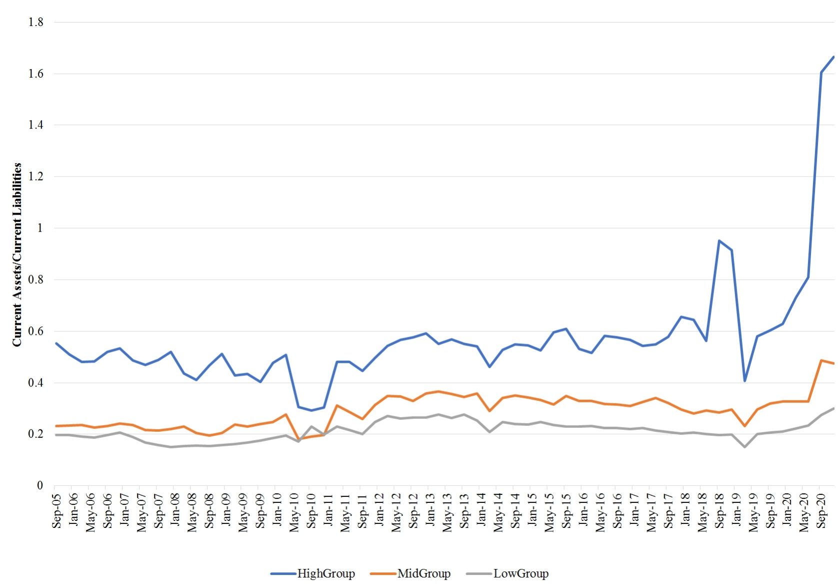

Figure 13: Liquidity Ratio

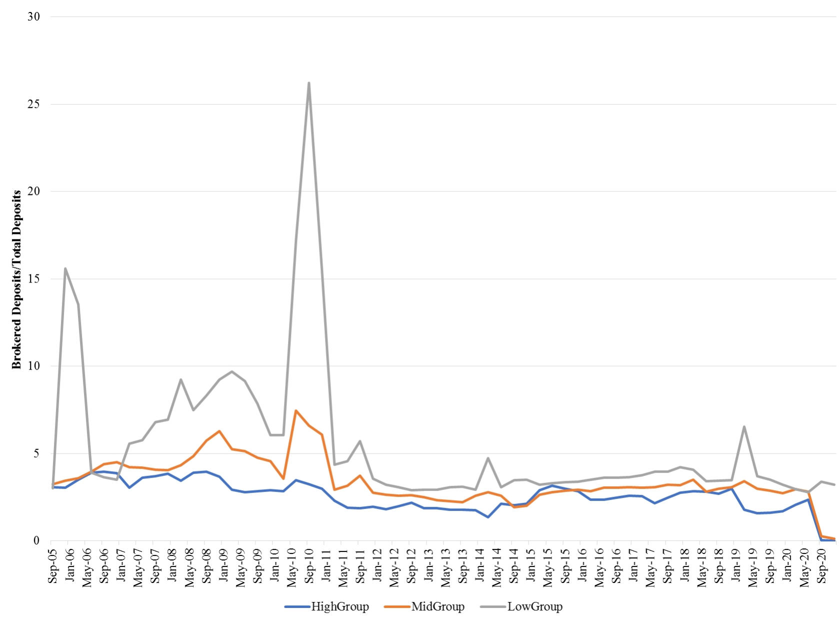

Figure 14: Brokered Deposits

Figure 14 shows the extent to which banks use brokered deposits to fund their lending operations. The use of such borrowed funds can be costly and used to fund riskier ventures. Once again, our analysis shows that lower-efficiency banks use brokered deposits to a greater extent than the most-efficient banks (Table 5).

In Figure 15, the level of net loans and leases (that is, total loans and leases minus the allowances for loan losses) that a bank puts on its balance sheet is shown for the three bank managerial efficiency cohorts. Similar to the high level of statistical significance that we found for nearly every time period between the high-efficiency and low-efficiency banks for the Tier 1 capital ratio (Figure 3), net loans and leases as a percentage of total assets also shows highly significant statistical differences between these two groups in 59 of the 62 quarters (Table 5). This seems to suggest that banks with lower managerial efficiency are less liquid because they have loaned out a greater portion of their funds.

6.5 Sensitivity to Market Risk

Understanding and measuring a bank's sensitivity to market risk using only balance sheet and income statement entries is difficult and can be misleading. The time-series data in Figure 16 shows off-balance sheet (OBS) risk-weighted assets to total risk-weighted assets. But how the banks are using off-balance sheet risk management tools is another question. If they are being used to hedge

Table 5: Liquidity, Sensitivity to Risk, and Failure Risk: High- Versus Low-Efficiency Banks, Differences in Means z-Test

	Liquidity						Sensitivity to Market Risk		Failure Risk	
	Liquidity Ratio		Brokered Deposits/ Total Deposits		Net Loans & Leases/ Total Assets		Off-Balance Sheet Assets/ Total Assets		Adjusted Texas Ratio	
Date	z-statistic	significance level	z-statistic	significance level	z-statistic	significance level	z-statistic	significance level	z-statistic	significance level
Sep-05	4.9688	***	0.17609		-12.5310	***	-6.7341	***	-118.0751	***
Dec-05	5.7671	***	-0.08381		-13.4726	***	-5.3936	***	-116.1153	***
Mar-06	10.6560	***	-0.09956		-15.7245	***	-6.7215	***	-136.8427	***
Jun-06	10.1872	***	0.01611		-14.5142	***	-6.1018	***	-68.5225	***
Sep-06	8.5088	***	0.69117		-15.1974	***	-5.0552	***	-76.1340	***
Dec-06	9.7766	***	0.85562		-15.1292	***	-5.1324	***	-58.5551	***
Mar-07	11.5125	***	-5.79390	***	-17.8163	***	-4.5872	***	-103.7960	***
Jun-07	11.0735	***	-5.06359	***	-19.9162	***	-3.9178	***	-93.8097	***
Sep-07	10.0346	***	-6.53235	***	-21.7119	***	-2.0765	**	-104.7468	***
Dec-07	7.3531	***	-6.49702	***	-24.2880	***	-1.2835		-44.4160	***
Mar-08	19.9076	***	-8.03582	***	-22.3204	***	-3.8760	***	-88.9994	***
Jun-08	12.2348	***	-4.50692	***	-15.6129	***	-3.1377	***	-134.9187	***
Sep-08	3.8181	***	-6.70118	***	-19.1117	***	-1.6199		-102.6405	***
Dec-08	2.7633	***	-8.36445	***	-21.2232	***	-1.0971		-91.0044	***
Mar-09	23.8378	***	-13.75881	***	-27.0904	***	0.4069		-19.7949	***
Jun-09	9.4179	***	-13.63795	***	-25.2014	***	-0.4353		-1.3453	
Sep-09	17.4315	***	-10.81348	***	-22.4841	***	0.9568		-5.4039	***
Dec-09	4.5368	***	-7.74278	***	-23.7411	***	0.5928		-28.1058	***
Mar-10	3.5952	***	-7.63998	***	-23.0623	***	1.2598		-17.4712	***
Jun-10	6.5279	***	-0.19425		-0.2039		-7.3450	***	-18.2163	***
Sep-10	6.7294	***	-0.17998		0.0862		2.3841	**	-11.5849	***
Dec-10	17.8657	***	-0.37486		-0.0459		34.4389	***	-15.2294	***
Mar-11	12.4451	***	-5.47504	***	-21.2795	***	1.2580		-7.4778	***
Jun-11	11.6488	***	-8.44669	***	-21.3435	***	3.6638	***	-51.3487	***
Sep-11	4.7493	***	-8.25047	***	-15.5069	***	14.6312	***	-46.3425	***
Dec-11	10.2994	***	-4.27034	***	-18.1645	***	3.1950	***	-11.6459	***
Mar-12	10.3743	***	-4.07420	***	-19.0319	***	2.7809	***	-22.9216	***
Jun-12	7.8067	***	-2.92364	***	-18.3616	***	4.1564	***	-24.5209	***
Sep-12	6.0694	***	-1.81519	*	-16.9593	***	4.2643	***	-5.2532	***
Dec-12	8.1348	***	-2.78370	***	-19.1084	***	2.9831	***	-33.7461	***
Mar-13	8.7615	***	-2.82401	***	-19.9445	***	3.3023	***	-10.2349	***
Jun-13	8.0849	***	-3.39897	***	-19.8843	***	3.6613	***	-32.0522	***
Sep-13	7.3795	***	-3.50320	***	-19.0881	***	4.1360	***	-27.4025	***
Dec-13	8.0634	***	-3.14302	***	-19.9920	***	5.8981	***	-3.2481	***
Mar-14	15.1910	***	-14.12263	***	-27.9901	***	14.0289	***	-20.8039	***
Jun-14	10.5845	***	-2.27423	**	-19.3595	***	5.4775	***	-15.7321	***
Sep-14	10.3531	***	-3.38201	***	-19.9072	***	5.7572	***	-13.2647	***
Dec-14	10.1124	***	-3.08053	***	-19.4415	***	4.0771	***	-23.3342	***
Mar-15	10.4332	***	-0.63617		-18.3476	***	3.7697	***	-7.6651	***
Jun-15	6.0532	***	-0.26100		-17.3276	***	5.9293	***	-13.4324	***
Sep-15	5.9508	***	-0.66848		-16.2191	***	4.6342	***	-17.2545	***
Dec-15	9.3290	***	-1.03321		-16.3820	***	6.7725	***	-17.9821	***
Mar-16	8.4358	***	-2.34075	**	-16.7711	***	4.7276	***	-15.8780	***
Jun-16	5.5463	***	-2.48878	**	-17.1383	***	6.6320	***	-6.3281	***
Sep-16	6.0669	***	-2.31170	**	-15.7465	***	6.5706	***	-11.9400	***
Dec-16	6.8378	***	-2.12501	**	-16.8360	***	6.3837	***	-6.0895	***
Mar-17	7.7332	***	-2.34674	**	-18.1107	***	6.3345	***	-11.1559	***
Jun-17	7.1249	***	-3.90950	***	-18.0887	***	4.3604	***	-10.5735	***
Sep-17	6.6857	***	-3.09632	***	-17.3840	***	7.5776	***	-17.0781	***
Dec-17	3.4126	***	-2.97038	***	-18.3294	***	3.8492	***	-20.9213	***
Mar-18	3.8417	***	-2.51912	**	-17.8508	***	4.4290	***	-23.0703	***
Jun-18	6.4850	***	-1.17515		-16.8868	***	4.3631	***	-20.3642	***
Sep-18	1.8830	*	-1.50773		-16.8829	***	4.6151	***	-15.8430	***
Dec-18	1.9368	*	-0.99534		-17.4098	***	4.8034	***	-14.2513	***
Mar-19	13.7128	***	-14.06216	***	-27.4582	***	18.9743	***	-15.5152	***
Jun-19	6.4935	***	-6.89962	***	-18.6425	***	4.9549	***	-20.9692	***
Sep-19	5.9330	***	-5.95714	***	-18.3182	***	-7.5817	***	-21.9724	***
Dec-19	5.6491	***	-4.52750	***	-18.1699	***	6.3662	***	-19.6729	***
Mar-20	3.2892	***	-2.22414	**	-17.8671	***	-5.4404	***	-15.8928	***
Jun-20	3.2098	***	-1.06233		-17.4232	***	3.4410	***	-14.8357	***
Sep-20	2.1872	**	-92.82528	***	-13.9590	***	-3.2481	***	-16.9860	***
Dec-20	2.2746	**	-88.38741	***	-15.8755	***	10.6448	***	-19.9957	***

	***	58	***	36	***	59	***	51	***	61
	**	2	**	8	**	0	**	2	**	0
	*	2	*	1	*	0	*	0	*	0
	not signif.	0	not signif.	17	not signif.	3	not signif.	9	not signif.	1

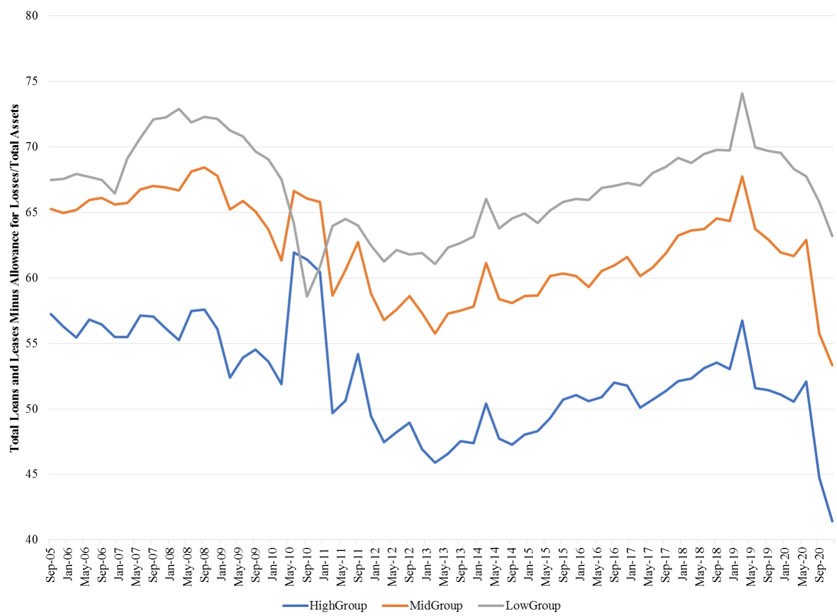

Figure 15: Net Loans and Leases Concentration

against interest rate risk and other potential risks, then a high concentration of OBS activities may be warranted. But if used for speculation, then there may be increased levels of risk. Interestingly, the high-efficiency banks appear to have a higher concentration of OBS risk-weighted assets than the lower-efficiency banks, at least since the 2008-09 financial crisis.

6.6 Failure Risk

Figure 17 shows the adjusted Texas ratio, a metric created in the late 1980s during Texas' financial crisis, that measures the level of a bank's non-performing assets as a percentage of its Tier 1 capital, adjusted here to also include its loan loss reserve. This is perhaps the most important metric and figure in this paper. The statistical differences between the high-efficiency banks and the low-efficiency banks are highly significant in 61 of 62 quarters, with only one quarter during the 2008-09 financial crisis not signaling a significant difference (Table 5).

6.7 Putting It All Together

Table 6 summarizes the level of statistically significant differences using the z-test to compare the mean values for 15 bank performance and risk metrics for the high-efficiency banks and the low-efficiency banks across 62 quarters from

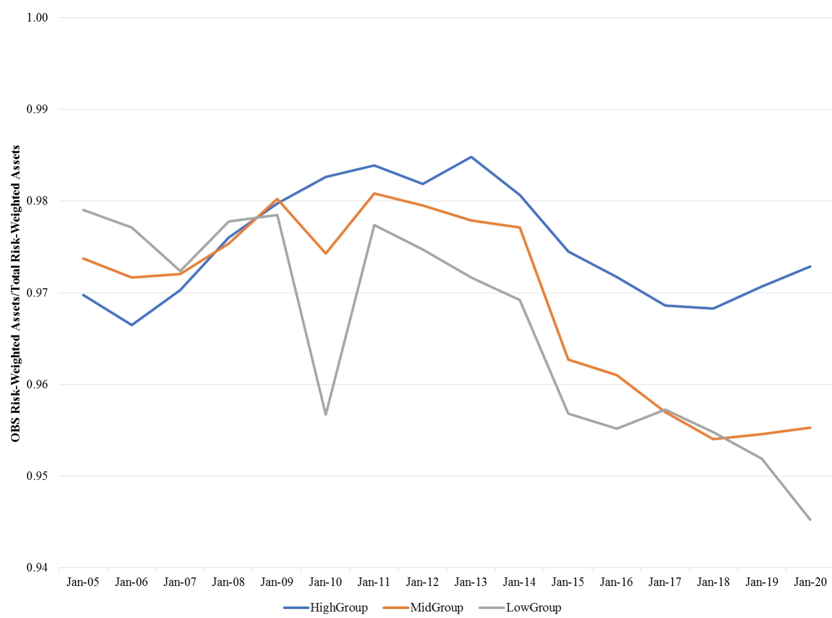

Figure 16: Off-Balance Sheet Risk-Weighted Assets

the third quarter 2005 to the fourth quarter 2020. The overall results show that there were 670 (72%) highly significant differences (that is, at the 0.01 level of significance) between the high- and low-efficiency banks, out of a possible 930 observations. Only 141 (15%) of the observations showed no statistically significant difference.

Across time, it appears that observations since the 2008-09 financial crisis suggest the highest level of significant statistical differences between high- and low-efficiency banks. From the beginning of our series through 2010, an average of 9.6 metrics (64%) exceeded the highly significant statistical difference between high- and low-efficiency banks. Since then, an average of 11.5 metrics (76%) exceeded this threshold.

And while all of these variables show at least some level of statistical difference between the high- and low-efficiency banks, we find a few metrics that exhibit highly significant statistical differences in nearly all time periods. The most important metrics are the differences exhibited for the adjusted Texas ratio, the Tier 1 capital ratio, the net loans and leases to total assets ratio, the liquidity ratio, and the interest expense to average assets ratio. All of these metrics had at least 58 of 62 quarters with highly significant statistical differences.

Other noteworthy metrics with at least 50 quarters of highly significant statistical differences between the high- and low-efficiency banks include commercial and industrial loans to total risk based capital, past due and nonaccrual

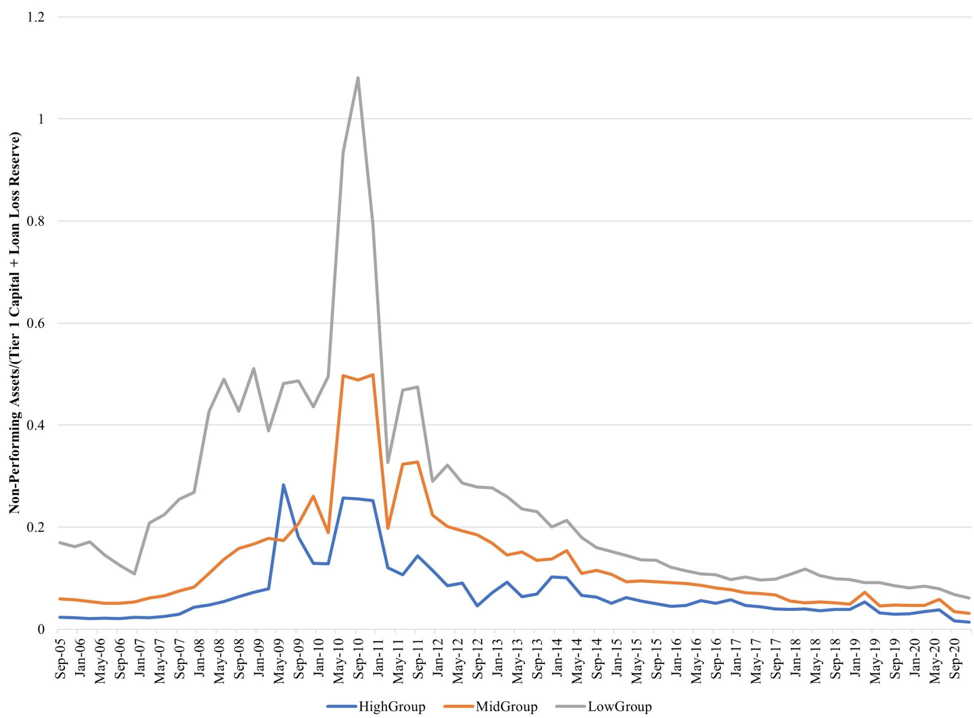

Figure 17: Adjusted Texas Ratio

Table 6: Summary of Significant Difference Levels, by Quarter, for All 15 Metrics, High- vs. Low-Efficiency Banks

Total Significance Levels for All 15 Metrics

Date	***	**	*	No Signif.
Sep-05	7	1	1	6
Dec-05	6	2	1	6
Mar-06	10	1	1	3
Jun-06	10	1	0	4
Sep-06	9	1	3	2
Dec-06	12	2	0	1
Mar-07	9	1	0	5
Jun-07	11	2	0	2
Sep-07	10	2	1	2
Dec-07	10	2	0	3
Mar-08	9	1	1	4
Jun-08	10	0	0	5
Sep-08	10	2	1	2
Dec-08	11	2	0	2
Mar-09	12	1	0	2
Jun-09	11	1	1	2
Sep-09	10	2	1	2
Dec-09	13	1	0	1
Mar-10	11	3	0	1
Jun-10	8	0	0	7
Sep-10	5	2	0	8
Dec-10	8	0	1	6
Mar-11	10	2	1	2
Jun-11	12	2	1	0
Sep-11	12	0	1	2
Dec-11	14	0	0	1
Mar-12	14	0	0	1
Jun-12	14	0	0	1
Sep-12	12	1	1	1
Dec-12	14	0	0	1
Mar-13	11	2	0	2
Jun-13	13	2	0	0
Sep-13	13	1	0	1
Dec-13	12	2	1	0
Mar-14	11	3	1	0
Jun-14	11	3	0	1
Sep-14	12	2	1	0
Dec-14	13	1	0	1
Mar-15	11	0	1	3
Jun-15	12	0	1	2
Sep-15	11	0	1	3
Dec-15	12	0	0	3
Mar-16	9	2	2	2
Jun-16	9	3	1	2
Sep-16	10	2	0	3
Dec-16	10	2	0	3
Mar-17	9	2	1	3
Jun-17	9	2	3	1
Sep-17	11	2	0	2
Dec-17	12	1	0	2
Mar-18	10	3	0	2
Jun-18	11	1	0	3
Sep-18	11	0	1	3
Dec-18	9	2	1	3
Mar-19	11	4	0	0
Jun-19	14	0	0	1
Sep-19	13	1	0	1
Dec-19	13	1	0	1
Mar-20	10	3	1	1
Jun-20	8	0	1	6
Sep-20	11	2	1	1
Dec-20	14	1	0	0
	***	**	*	No Signif.
	670	85	34	141

loans to total loans, and OBS risk-weighted assets to total risk-weighted assets (although this metric showed significant differences in both directions).

7 Conclusions and Recommendations for Future Research

In conclusion, we find that banks closest to the DEA managerial efficiency frontier are better-off. Banks with higher DEA efficiency scores appear to be less likely to fail as measured by the adjusted Texas ratio. According to several bank performance and risk metrics, such banks have higher Tier 1 capital ratios, stronger liquidity positions, healthier asset quality, and better profitability.

As a benchmarking performance metric, DEA could help lower-efficiency banks better understand the sources of their inefficiency and what they might be able to do to get closer to the efficient frontier. As an examiner tool, DEA could be used as a proxy for the "M" (management quality) in the CAMELS rating framework and used along with other off-site monitoring tools to flag institutions that might require further investigation and review.

Our recommendations for future academic research are as follows. First, the DEA managerial efficiency model presented herein is sensitive to the variables selected and the weights used in the constraints. A better understanding of the right set of variables, weights, and their sensitivity to final values is needed. Second, The DEA managerial efficiency scores calculated using our model could be added as a variable to existing bank failure prediction models to see if it adds significance and predictive abilities to examiner off-site surveillance tools. And third, researchers with access to confidential bank examiner ratings could use our DEA model to see how well DEA efficiency scores correlate with composite CAMELS ratings and the "M," or management quality rating, given by bank examiners.

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