The Relationship Between the Dodd-Frank Act and the Cost Efficiency of U.S. Banks

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Abstract

Motivated by the regulatory changes imposed by the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010, this study explores the potential implications of this regulatory change to the cost efficiency of U.S. banks. The focus on the core cost efficiency of banks is driven by its ability to reduce the probability of failure. Using a parametric cost frontier methodology that measures how efficient a bank is relative to a best-practice frontier, this research shows that the ability of banks to minimize costs deteriorated on average by around thirteen percent after the Dodd-Frank Act was implemented. Given that this regulation imposed stricter regulatory restrictions on large banks, this study explores the potential heterogeneous impact of this policy across banks of different sizes. The findings imply that, although larger banks tend to be more efficient, stricter regulatory oversight decreases the efficiency gap between large banks and their smaller counterparts.

Keywords: Banking, Costs, Efficiency, Dodd-Frank Act, Bank Failure, Regulations.
JEL Classification: G28, G20, G21

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1 Introduction

Banking regulations are generally imposed to improve the efficiency of financial markets by reducing excess risk-taking behavior, improving financial fragility, and, consequently, increasing confidence in the financial system. Despite such goals, financial regulations can negatively impact bank performance since their regulatory burden requires banks to reallocate personnel or resources to adhere to the new supervision requirements. These changes in banks' compliance costs can put downward pressure on bank profitability (Feldman et al., 2013; Nippani and Ling, 2021). McLaughlin and Sherouse (2015) emphasize the magnitude of this regulatory change by showing that the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, hereon called the Dodd-Frank Act, almost doubled the number of banking regulatory restrictions previously under Title 12 of the Code of Federal Regulation.

The Dodd-Frank Act was signed into law by President Barack Obama in July 2010 as a response to the financial crisis that led to the Great Recession of 2009. This law strengthened regulatory capital and liquidity standards, limited proprietary trading, and limited investment in hedge funds or private equity funds for all banks, which had implications for bank performance and cost structure (Cyree, 2016; Hogan and Burns, 2019). Rather than focusing on U.S. banks' profitability, overall expenditures, or cost composition, we complement these studies by investigating if the Dodd-Frank Act affected bank cost efficiency. Given the reported impact of the Dodd-Frank Act on banks' cost structure, we hypothesize that they experience a lower relative cost efficiency in this new regulatory environment.

Motivated by non-uniform restrictions imposed by this federal law on banks due to differences in total assets, we contribute to this strain of literature exploring the heterogeneous effect of this regulation across banks of different sizes. The Dodd-Frank Act mainly targeted banks with at least \$10 billion and \$50 billion in total assets by imposing self- and Federal Reserve-administered stress tests, in addition to higher risk management and regulatory oversight (Board of Governors of the Federal Reserve System, 2012; Bindal et al., 2020). However, banks with at least \$50 billion in total assets faced stricter restrictions and semi-annual rather than annual stress tests.[1] Given that such tests require banks to hire or reallocate resources to establish risk committees to comply with the new regulatory burden (Hogan and Burns, 2019), we explore whether banks above such size threshold had their ability to minimize costs affected more than their peers.

Bank cost efficiency has implications for its profitability, survival, and, potentially, overall financial stability. In addition to determining how well banks are cost-minimizing, cost efficiency also provides information on the quality of bank managers responsible for creating strategies to minimize bank expenditures relative to its total

[1] This threshold was increased to \$250,000 by the Office of the Comptroller of the Currency (OCC) in 2019. We discuss some of the implications of this change in Section 6.

output (Elyasiani and Mehdian, 1990). This performance indicator is a better proxy for management quality than profit efficiency, which emphasizes the relevance of this measurement for bank regulators. Assaf et al. (2019) document that profit efficiency can be misleading to regulators because it can be temporarily driven by high returns from risky investments.

To estimate the core cost efficiency of U.S. banks, we apply a parametric cost frontier methodology using data from 2004 to 2016 for U.S. banks insured by the FDIC. We opt for a parametric model over a non-parametric one due to its ability to disentangle the bank inefficiency component from the error term and predict bank failures (Assaf et al., 2019). We estimate cost functions while enabling firm efficiency to be persistent over time. Based on our preferred model specification, our estimates imply that implementing the Dodd-Frank Act lowered U.S. banks' average relative cost efficiency by around thirteen percent.

This is the first study to use a comprehensive cost-efficiency measurement associated with banks' financial fragility to examine how the Dodd-Frank Act affected the efficiency gap between large banks and their counterparts. Even though Sakouvogui and Shaik (2020) explored the impact of the Dodd-Frank Act on bank cost efficiency, the authors do not investigate its heterogeneous effect on banks of different sizes. Their time-varying efficiency measurement does not account for the persistence of bank efficiency over time (Berger and Mester, 1997), which could explain why such an empirical framework has not been linked with predicting bank failures. Given that different methodologies can generate different results (Greene, 2005), a methodology that can predict bank failure is especially relevant to producing valuable insights into the economic implications of this policy.

Using a Tobit regression including bank and market characteristics, this research provides a descriptive analysis showing that despite being more cost-efficient, this regulation had a more substantial negative effect on the ability of targeted banks (at least $50 billion in assets) to minimize costs. We argue that this adverse effect on the performance gap of larger banks arises due to the higher regulatory burden they face. This study provides empirical evidence that one of the potential indirect effects of the Dodd-Frank Act is a decrease in the disparity in cost efficiency across banks of different sizes. The results complement Bindal et al. (2020), who focus on how this regulation altered the acquisition behavior of banks at the regulatory size threshold.

In addition, this study reports that liquidity, risk-taking behavior, age, specialization in cyber offices, regulators, and market characteristics also explain differences in bank performance. Our empirical strategy follows a similar methodology from Akhigbe and McNulty (2005), who study potential correlates of profit efficiency. By examining the relationship between a bank's share of offices specialized in cyber services and its ability to minimize costs, this research also complements Cyree et al. (2009), who report that specialization in internet services is associated with higher bank returns. Given that the relationship between office specialization in online services and cost efficiency is not robust across all regression models, our results suggest that this bank strategy is more likely to positively impact the ability of banks to increase revenue rather than to minimize costs.

2 Literature Review

Given that this study is concerned with exploring the effects of the Dodd-Frank Act on banking cost efficiency, in this section, we review studies related to the impact of this regulatory change on U.S. banks' cost structure and efficiency. We leave the literature review on cost efficiency methodologies to be presented within the introduction of the empirical framework in Section 4.

A change in regulation can lead to direct and indirect effects on institutions. Bartel and Thomas (1985) describe that direct effects refer to changes in firms' cost structure, performance, and risk-taking behavior. In contrast, indirect effects refer to the competitive advantages that can develop due to the asymmetrical impact of a regulation across different firms. Some of the Dodd-Frank Act's direct effects include increased capital and regulatory compliance costs due to banks redirecting resources toward getting legal assistance to interpret the regulatory changes and create strategies to comply with the new law and stress tests.

For instance, Hogan and Burns (2019) show that non-salary expenses on legal counsel, consulting, auditing, and data processing increased for small financial institutions, while larger ones particularly experienced increases in legal and data processing expenses. Expenditures on salaries also increased following the implementation of this law (Dolar and Dale, 2020), while technology adoption, loans per employee, and bank profitability were negatively impacted (Cyree, 2016). Nippani and Ling (2021) provide further empirical evidence on the impact of this regulatory change on bank performance. The authors explore a larger set of performance measures (such as debt ratios, net interest margin, net loan losses, and nonperforming loans) and find that they worsened post-implementation of the Dodd-Frank Act.

Similar to this study, Sakouvogui and Shaik (2020) investigate how this regulation impacted the cost efficiency of banking institutions; however, this research differs from theirs in two aspects. First, we explore the asymmetric impact of this regulatory change on targeted vs non-targeted banks. Thus, we contribute to the literature by investigating the indirect effects of the Dodd-Frank Act by exploring its heterogeneous impact across banks of different sizes. Second, we use a methodology of greater relevance to policymakers, given that it is empirically linked to the financial fragility of U.S. banks.

Buchanan and Tullock (1975) and Klomp and de Haan (2012) discuss the importance of the heterogeneous firm model of regulation, highlighting how a one-size-fits-all regulatory regime can create winners and losers when firms are not homogeneous. The authors argue this is due to the same regulatory compliance action potentially having different implications for different firms. The Dodd-Frank Act recognizes the importance of differentiating regulatory restrictions across banks of different sizes due to differences in the importance of these large banks to overall financial fragility; thus, it distinguishes the magnitude of regulatory requirements imposed on such banks. In addition to size, bank location and asset specialization also play an important role in the regulatory burden faced by financial institutions (McKee and Kagan, 2019). McKee and Kagan find that the Dodd-Frank Act had asymmetric implications for rural real estate specialized lenders' costs (noninterest expenses to assets) and income (noninterest income to income) structure. Motivated by these studies, we use a sophisticated measure of core cost efficiency to evaluate the indirect effects of the Dodd-Frank Act by assessing if the gap in efficiency between banks of different sizes changed after controlling for banking market characteristics.

3 Data

Several data sources were used to evaluate the research question proposed in this article. This study defines U.S banks as all domestic financial institutions with deposits insured by the FDIC. Banking data comes from three sources. Consolidated banking data comes from the Call Report Data and Summary of Depository Institutions (SDI) data reported by the Federal Financial Institutions Examination Council (FFIEC). These are quarterly unbalanced micro banking time series data sets containing information about these institutions' balance sheets and income statements. Moreover, bank branch-level data is reported yearly and contains information on branch location, level of deposits per branch, and bank regulator. The branch-level data comes from the Summary of Deposits (SOD) data set produced by the FDIC.

In addition to using asset size to characterize large banks, we produce results that include only community banks. Community banks represent a relatively homogeneous group of banks that tend to be small (less than $1 billion in assets), focus on the provision of traditional banking services (gathering deposits and making loans), and operate in more geographically constrained areas (Federal Deposit Insurance Corporation, 2012). Given their local nature, an analysis including only these banks enhances the effectiveness of controls for banking market characteristics.

As discussed by Assaf et al. (2019), this study's parametric cost frontier methodology requires six years of quarterly data pre- and post-regulatory change to generate plausible results. Hence, since the Dodd-Frank Act was imposed in early 2011, we choose the period from 2005 to 2016 to create reasonable estimates of bank cost efficiency while considering its persistence over time. Our unbalanced banking data set contains 339,943 observations and 9,269 banks – 8,586 banks with at least one observation before the Dodd-Frank Act and 7,472 after its implementation. This decrease in the number of banks follows the known consolidation trend of the banking industry.

We annualize income statement variables when necessary. At the regional level, annual population data is extracted from the U.S. Census, while median yearly income comes from the U.S. Bureau of Labor Statistics. When applicable, banking and regional variables are adjusted for inflation using the GDP implicit price deflator (base year 2018:Q1) reported by the Bureau of Economic Analysis (BEA).

4 Methodology

From a neoclassical producer theory perspective, a necessary condition for a firm to maximize profits is minimizing costs (Flannery, 1982). In this framework, a firm will choose the output level that maximizes profit, assuming it will select the input bundle that minimizes the cost of producing that output level at current input prices. This methodology estimates the difference between a firm's total cost and the minimized total cost from the predicted optimized cost frontier, the composite error term. Despite several econometric techniques having the ability to estimate the cost frontier and, hence, firms' inefficiency, they all face certain advantages and pitfalls. This study will focus on the parametric cost frontier estimation, which is motivated and described below.

4.1 Cost Efficiency Estimation for Banks

In a banking application, given that banks have a business model that involves using deposits to make loans, a bank's production cost depends on the costs associated with gathering such funds. However, in this setting, since the underlying technology of these firms' production process is unobserved, efficiency is generally defined relative to the best-practice competitor in the industry. Therefore, in this study, we define bank cost-efficiency as the ratio between its inefficiency component and the inefficiency component of its best-practice peer if it was facing the same environmental conditions and input bundle prices.

Methods applied to estimate the cost efficiency of U.S. banks varied between parametric and nonparametric since the 1990s (Aiello and Bonanno, 2018). Berger and Mester (1997) emphasize two main advantages of parametric methods. First, they consider input prices and, thus, capture both the technical and allocative efficiency skills of a bank. Allocative efficiency is associated with properly responding to relative prices when choosing bundles of inputs and outputs for production, while technical efficiency focuses on maximizing output while minimizing expenses. Second, the nonparametric approach cannot disentangle the composite error term's inefficiency and random error term components. Hence, it carries the risk of confusing random deviations with bank inefficiency, which is addressed by the parametric approach by making explicit assumptions about their distributions.

Bauer and Hancock (1993) highlight concerns about the validity of setting distributional assumptions for the distribution of the composite error term when investigating U.S. banks.[2] Nonetheless, Berger (1993) reports that these concerns are minimized if panel data is available since the Distribution-Free Approach (DFA) becomes an option. In the DFA parametric estimation, one first assumes that each bank has a core, or average, efficiency over the period under study. Such efficiency can be set apart from its temporary fluctuations due to the assumption the model imposes that such fluctuations average out to zero over time. For this assumption to hold, Berger and Mester (1997) and DeYoung (1997) show that the selection of 6 years is optimal.[3] Combined with the ability to disentangle random errors from bank performance, our focus on evaluating a bank's economic rather than only technical optimization process motivates using the parametric estimation in our analysis. Our model specification to Assaf et al. (2019)'s given that it produces estimates that are inversely linked with the probability of a bank failure during a financial crisis.

The cost function chosen is defined to be dependent on the vectors w of given input prices, q of given output quantities, and the composite error. The composite error term can then be decomposed between the inefficiency component, u, and a random error term, ε. In a banking application, the vectors z and υ are also included in the model to control for potential scale bias and environmental factors, respectively. In this case, we note that the vector of input quantities can be omitted in the estimation process. This can be derived by solving the Kuhn-Tucker conditions from a bank's economic cost minimization problem, which illustrates that the vector with the input levels is a function of both w and q.

The total short-run cost function of a bank is then written as:

$$C_{it} = F(w_{it}, q_{it}, z_{it}, \upsilon_{it}, u_{it}, \varepsilon_{it}), \tag{1}$$

which allows one to derive the relative core cost efficiency of a bank i, $\hat{E}_i$, through Equation 2,

$$\hat{E}_i = \frac{\hat{C}_{min}}{\hat{C}_i} = \frac{\exp\left[\hat{c}\left(w_i, q_i, z_i, \upsilon_i\right)\right] \times \exp\left[\ln \hat{u}_{min}\right]}{\exp\left[\hat{c}\left(w_i, q_i, z_i, \upsilon_i\right)\right] \times \exp\left[\ln \hat{u}_i\right]} = \frac{\hat{u}_{min}}{\hat{u}_i} \qquad with\, \hat{E}_i \in (0, 1], \tag{2}$$

where, $\hat{u_{\min}} = \min\{\hat{u_{i_1}}, \hat{u_{i_2}}, ..., \hat{u_N}\}$ and N refers to the number of banks in the sample.

[2] Earlier research commonly assumed the composite error term followed a half-normal distribution.

[3] Even though the results presented use 6-year intervals of quarterly micro-level U.S. banking data set to estimate bank efficiency, bank cost efficiency is also assessed using intervals of 5.5 and 6.5 years. The results are robust and can be provided upon request.

4.1.1 Input Prices and Output Variables

This study's output and input selection follow the arguments favoring modern banking theories in which banks intermediate deposits into loans and engage in off-balance sheet activities (Assaf et al., 2019). We define the total costs experienced by banks by the sum of their interest and noninterest expenses. The noninterest expenses considered include the price of labor (total personnel expenses per full-time employee), w_1, the price of physical capital (total operating and administrative expenses relative to total premises and fixed assets), w_2, the price of purchased funds, w_3, and the price of core deposits, w_4. A bank's output is then calculated by the sum of the value of its total consumer loans, y_1, commercial and industrial (C&I loans), y_2, residential real estate loans, y_3, commercial real estate loans, y_4, and all other loans, y_5. Moreover, z is composed of z_1 and z_2, which define the notional value of a bank's off-balance sheet activities and its level of financial equity capital, respectively.[4]

Lastly, υ accounts for the risk exposure a bank faces, which is approximated here by the share of nonperforming loans in the market in which a bank operates. This is estimated by the weighted average of the share of nonperforming loans of banks operating in each state (Berger and DeYoung, 1997; Assaf et al., 2019). We use each bank's share of *total state deposits* to determine the weight of a bank in a state. For a bank operating in more than one state, we calculate its weighted average of state nonperforming loans using the share of total deposits of that bank as a weight for each state it operates in. Given that recent studies have emphasized the relevance of considering counties as good approximates of banking markets (Danisewicz et al., 2018; Shim, 2019), we also run robustness checks using counties instead of states to define banking markets. The cost-efficiency estimates are robust to both υ specifications.

To diminish concerns that these environmental risk controls are inappropriate for banks operating in multiple states, we also produce estimates of cost efficiency considering only community banks. Estimates focusing on community banks reduce concerns with potential imperfections of υ. For estimates including only community banks, this state-level exposure is estimated using the share of non-performing loans of community banks operating in each state. Once again, we also run robustness checks with county-level environmental risk controls.

Table 1 summarizes information on the variables included in the cost estimation. Given that the Dodd-Frank Act was signed into law in 2010, we use the first quarter of 2011 as the beginning of the post-Dodd-Frank Act period. We observe an increase in the average expenditure per worker due to the need to reallocate personnel to comply with new restrictions and stress tests imposed by the Dodd-Frank Act. We also note a decrease in the share of assets allocated toward loans. This table shows the potential impact of this regulation on bank costs and asset allocation and motivates the re-exploration of the cost efficiency of U.S. banks. The following sub-section

[4] Equity directly affects the cost of providing an alternative to deposits as a funding source for loans. Interest paid on debt is an expense, but dividends paid are not; nonetheless, raising equity is more costly than raising deposits.

describes the cost function used in this study in more detail before presenting our estimates.

Table 1: Descriptive Statistics of the Cost Function Main Variables

	Pre-Dodd-Frank Act		Post-Dodd-Frank Act	
Variable	Mean	Sd. Dev.	Mean	Sd. Dev.
Price of labor	67.989	31.950	73.968	34.657
Price of physical capital	0.494	8.752	0.609	24.731
Price of purchased funds	0.040	0.098	0.045	0.228
Price of core deposits	0.047	5.395	0.015	0.865
Consumer loans	0.056	0.080	0.036	0.067
C&I loans	0.112	0.088	0.085	0.073
Residential real estate loans	0.207	0.151	0.203	0.153
Commercial real estate loans	0.331	0.191	0.276	0.152
Other loans	0.063	0.099	0.055	0.087
Notion of off-balance sheet activities	0.060	3.334	0.106	5.298
Total equity capital	0.137	0.087	0.124	0.068
State bank's ratio of nonperforming loans	0.044	0.051	0.033	0.029
Observations	181,221		158,609	

[1] Price of labor is reported in thousands of real dollars.

[2] $y_{\#}$ and $z_{\#}$ variables are reported as share of total bank assets.

[3] For banks operating in more than one state, nonperforming loans represent the weighted average of the share of nonperforming loans based on its deposit share across all the states it operates in.

4.1.2 Cost Function Specification

As common in this approach, the inefficiency and random error terms are assumed to be multiplicatively separable from the cost function. Hence, we can re-write equation 1 as:

$$\ln C_{it} = c(w_{it}, q_{it}, z_{it}, \upsilon_{it}) + \ln u_{it} + \ln \varepsilon_{it}. \tag{3}$$

We opt for the Fourier-flexible functional form, which complements the standard second-order translog function specification by adding Fourier trigonometric terms. Thus, function c represents the natural log of function F in equation 1. Berger and Mester (1997) and Assaf et al. (2019) emphasize how this is the optimal functional choice for the cost estimation of banks, given its higher flexibility relative to the traditional translog approach. The authors argue that this model specification serves as a global approximation to virtually any cost function.

The cost function we specify for empirical estimation is defined by the Equation 4,

$$
\begin{aligned}
\ln\left(\frac{C}{w_4 z_2}\right) = {} & \delta + \sum_{h=1}^{3} \beta_h \ln\left(\frac{w_h}{w_4}\right) + \frac{1}{2}\sum_{h=1}^{3}\sum_{j=1}^{3} \beta_{hj} \ln\left(\frac{w_h}{w_4}\right)\ln\left(\frac{w_j}{w_4}\right) \\
& + \sum_{k=1}^{5} \gamma_k \ln\left(\frac{q_k}{z_2}\right) + \frac{1}{2}\sum_{k=1}^{5}\sum_{m=1}^{5} \gamma_{km} \ln\left(\frac{q_k}{z_2}\right)\ln\left(\frac{q_m}{z_2}\right) + \delta_1 \ln\left(\frac{z_1}{z_2}\right) \\
& + \frac{1}{2}\delta_{11} \ln\left(\frac{z_1}{z_2}\right)\ln\left(\frac{z_1}{z_2}\right) + \frac{1}{2}\sum_{h=1}^{3}\sum_{k=1}^{5} \lambda_{hk} \ln\left(\frac{w_h}{w_4}\right)\ln\left(\frac{q_k}{z_2}\right) \\
& + \sum_{h=1}^{3} \rho_h \ln\left(\frac{w_h}{w_4}\right)\ln\left(\frac{z_1}{z_2}\right) + \sum_{k=1}^{5} \tau_k \ln\left(\frac{q_k}{z_2}\right)\ln\left(\frac{z_1}{z_2}\right) + \sum_{n=1}^{9} [\phi_n \cos(x_n) + \omega_n \sin(x_n)] \\
& + \sum_{n=1}^{9}\sum_{g=1}^{9} [\phi_{ng} \cos(x_n + x_g) + \omega_{ng} \sin(x_n + x_g)] \\
& + \sum_{n,n',n''=1}^{9} [\phi_{nn'n''} \cos(x_n + x_{n'} + x_{n''}) + \omega_{nn'n''} \sin(x_n + x_{n'} + x_{n''})] \\
& + \zeta_1 \ln \upsilon + \ln u + \ln \varepsilon.
\end{aligned}
\tag{4}
$$

We estimate the total cost frontier for each bank, i, using panel data for the periods pre-Dodd-Frank Act and post-Dodd-Frank Act separately to derive the time-invariant bank-specific inefficiency component, the core inefficiency, for each sample. As standard in the literature, the subscripts i and t are omitted for easier visualization. The estimation does not include time fixed effects to account for the persistence of bank efficiency pre- and post-regulatory change.

Two standard normalization techniques are introduced in Equation 4. First, we normalize total costs and input prices by the average cost per dollar of core deposits to ensure linear homogeneity. This ensures that total costs move proportionally to changes in the cost of all input prices. Moreover, the normalization of total costs, output quantities, and z_1 by z_2 ensures the comparability among banks by reducing the risk of scale bias on the regression results. The common symmetry, homogeneity, and adding-up constraints are also imposed in the estimation procedure.

Lastly, two winsorizing approaches are implemented to reduce the impact of extreme outliers on the results. We winsorize by 10% the end of each interval, $[0, 2\pi]$, of x_n to reduce approximation problems near the distribution endpoints. The x_n's are rescaled terms of the $ln(w_h/w_4)$, $ln(y_k/z_2)$, and $ln(z_1/z_2)$.[5] In addition, the literature also highlights the possibility of outliers due to the inability of the model to purge out the random error through averaging completely. As a response, previous papers winsorize the distribution of the banks' estimated core inefficiency component at the 95th percentile prior to deriving a bank's relative cost efficiency through Equation

[5] As Assaf et al. (2019), we define x_n as $(0.2 \times \pi - \mu \times a + \mu \times variable)$, where $[a, b]$ is the range of the $variable$ being transformed and $\mu = (0.9 \times 2\pi - 0.1 \times 2\pi)/(b - a)$.

2. Due to improvements in the quality and quantity of data available for U.S. banks over the past two decades, we also generate results using the 99th percentile winsorizing approach for comparison. As common in the banking efficiency literature (Berger and Mester, 1997; Akhigbe and McNulty, 2005; Assaf et al., 2019), we omit detailed regression results for the cost function specified above, which can be provided upon request. Instead, we provide a summary of the results for our cost-efficiency estimates in the next section.

5 Results

This section is divided into two subsections to report the results clearly and concisely. First, we report the descriptive statistics of cost efficiency estimates for all U.S. banks and community banks pre- and post-Dodd-Frank Act. We then explore the impact of this regulation using a Tobit regression analysis to control for bank and market characteristics. To the best of our knowledge, this is the first study to investigate the potential heterogeneous impact of the Dodd-Frank Act on targeted vs. non-targeted banks using this core cost-efficiency methodology.

5.1 Bank-Level Cost Efficiency Results

The results of the cost efficiency estimation conducted are reported in Table 2 and Figure 1. We find that the average cost efficiency across U.S. banks decreased from 63.3 to 56.1% since the implementation of the Dodd-Frank Act when applying the 95th percentile winsorization approach traditionally used by the literature. Our results show that the relative ability of banks to minimize costs has significantly fallen since the mid-1990s from the 86.8% reported by Berger and Mester (1997). Figure 1 emphasizes how the distribution of cost efficiency shifts to the left in the new regulatory environment. Our estimates align with Assaf et al. (2019), who report an average relative bank cost efficiency of around 50% during financial crises. Given the authors' data set covers data until 2009, this study is the first to produce cost efficiency estimates using this parametric cost frontier specification using data post-Great Recession.

Despite the common use of the literature of the 95th percentile, we hereon opt to analyze only results based on 99th percentile estimates motivated by a couple of factors. First, Table 2 highlights how this stronger winsorization adjustment seems to shift the first and second moments of the distribution of banks' cost efficiency by affecting the firms selected as the best-performing banks in the sample for relative comparison. Figure 2 shows that the traditional winsorization approach does not smooth the distribution; instead, it truncates and creates a large aggregation of banks in both of its tails. Combined with a preference for staying closer to the actual data, these findings are technical contributions to the literature and justify why our preferred specification differs from

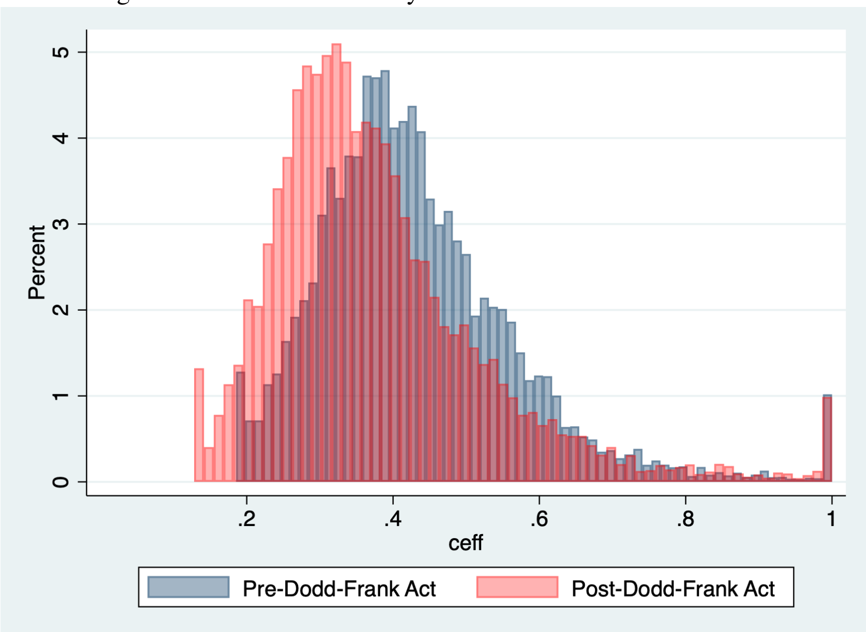
Table 2: Descriptive Statistics of Cost Efficiency Estimates

	Mean	Std. Dev.	Min.	Max.	N
All Banks:					
95th winsorization:					
Pre-Dodd-Frank Act	0.633	0.175	0.360	1.000	8,586
Post-Dodd-Frank Act	0.561	0.191	0.292	1.000	7,472
99th winsorization:					
Pre-Dodd-Frank Act	0.439	0.143	0.185	1.000	8,586
Post-Dodd-Frank Act	0.381	0.155	0.128	1.000	7,472
Community Banks:					
95th winsorization:					
Pre-Dodd-Frank Act	0.637	0.184	0.305	1.000	7,680
Post-Dodd-Frank Act	0.541	0.209	0.214	1.000	6,872
99th winsorization:					
Pre-Dodd-Frank Act	0.430	0.135	0.185	1.000	7,680
Post-Dodd-Frank Act	0.377	0.149	0.128	1.000	6,872

Pre-Dodd-Frank Act includes data from 2005 to 2010.

Post-Dodd-Frank Act includes data from 2011 to 2016.

Figure 1: Histograms of the Cost Efficiency of U.S. Banks Pre- and Post-Dodd-Frank Act

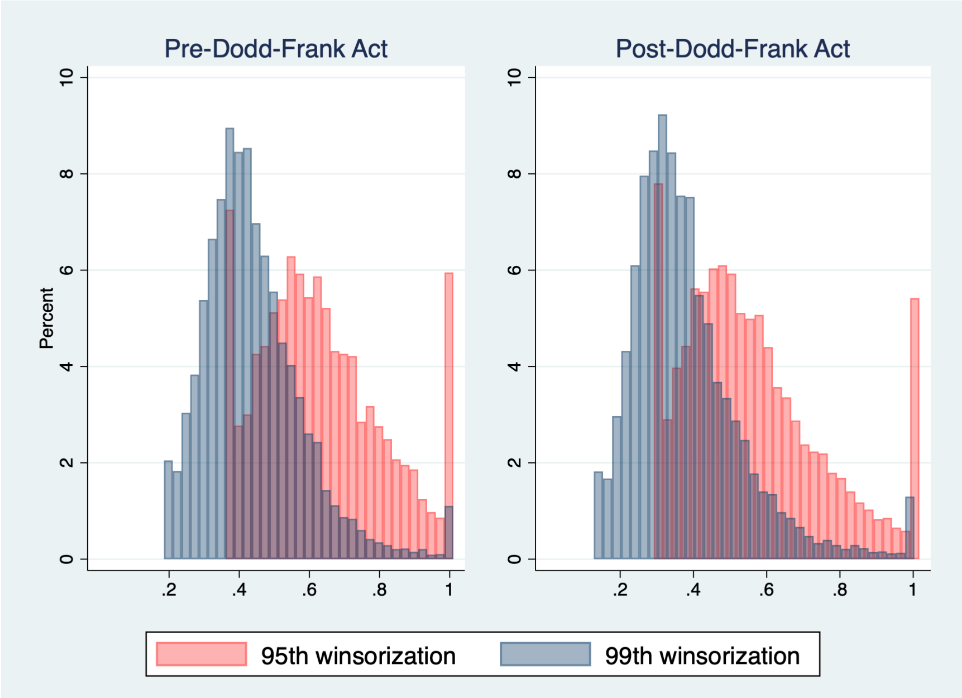


The pre-Dodd-Frank Act analysis includes data from 2005 to 2010. The post-Dodd-Frank Act analysis includes data from 2011 to 2016. The estimates reported use the 99th percentile winsorization approach.

the previous literature.

In the preferred specification, bank average cost efficiency decreased from 43.9 to 38.1%, a 13.2% decrease. Mean-comparison t-tests confirm that the pre- and post-Dodd-Frank Act cost efficiency averages are statistically different at the 99% confidence interval independent of the winsorization approach used and the bank sample

Figure 2: Histograms of the Cost Efficiency of U.S. Banks: Different Winsorization Approaches



Note: The pre-Dodd-Frank Act analysis includes data from 2005 to 2010. The post-Dodd-Frank Act analysis includes data from 2011 to 2016.

analyzed. We find that excluding non-community banks when estimating cost efficiency does not significantly alter our qualitative results.

This study emphasizes how different methodologies can produce different cost-efficiency results. For instance, our estimates are fairly lower than the average cost efficiency estimates around 85% presented by Sakouvogui and Shaik (2020), who uses a similar period but a time-varying cost efficiency parametric approach which does not take into consideration the time persistence of management quality and bank inefficiency. We prioritize using a methodology similar to Assaf et al. (2019) due to its advantage in improving the forecast of bank failures during a financial crisis, which provides real implications for the financial fragility of the banking system.

5.2 Empirical Investigation of Potential Correlates of Cost Efficiency

5.2.1 Regression Model Specification

In this section, we evaluate the robustness of our finding that the regulatory changes imposed by the Dodd-Frank Act decreased the ability of banks to minimize costs using regressions that control for differences in bank and market characteristics. We opt to use a Tobit model because bank cost efficiency is bounded between zero and one.

Since the cost-efficiency methodology applied produces time-invariant cost-efficiency estimates, time-varying variables included in this regression are expressed in six-year averages pre-Dodd-Frank and post-Dodd-Frank. Hence, in this analysis, a bank can only have up to two observations in the regression. Similar to Berger and Mester (1997), Pasiouras et al. (2009), and Sakouvogui and Shaik (2020), we present a descriptive rather than causal analysis of the relationship between bank cost efficiency with changes in the regulatory environment and its bank and market characteristics. The lack of causality inference arises from bank and market characteristics not being completely exogenous to bank cost efficiency.

We model $\hat{E}_{it}$, from Equation 2, to be explained by bank size ($Size_{it}$); the Dodd-Frank Act (DF); an interaction term between DF and $Size_{it}$; a vector of other bank characteristics (X_{it}); a vector of market characteristics (G_{it}); a common constant across banks (α_0); and a random error term (e_{it}). We cluster the standard errors at the bank level. Moreover, we consider the importance of comparing the performance of banks with similar lending models (Cyree et al., 2020) and evaluate our findings considering only community banks. In this model specification, we exclude non-community banks in both steps of our estimation approach, the cost efficiency estimation and the investigation of its potential determinants.

$$\hat{E}_{it} = \alpha_0 + \alpha_1 DF_{it} + \alpha_2 DF_{it} \times Size_{it} + \alpha_3 Size_{it} + \alpha_4 X_{it} + \alpha_5 G_{it} + e_{it} \tag{5}$$

To evaluate the relationship between the implementation of the Dodd-Frank Act and bank cost efficiency, we include a dummy variable equal to one called DF for all observations post-2010. The contribution of this paper comes from exploring whether the cost-efficiency gap for larger banks changed after the implementation of the Dodd-Frank Act, which we assess including an interaction term between DF and bank size, $Size_{it}$. Bank size is estimated using the log of a bank's average total assets before and after the implementation of this regulation.

Given the results reported by Sapci and Miles (2019) of a positive causal relationship between bank size and efficiency, we expect α_3 to be positive and significant. Nonetheless, since previous literature highlights that small banks experienced an increase in noninterest expenses greater than larger banks (Dolar and Dale, 2020), one may expect the coefficient α_2 also to be positive and significant. This study evaluates if previous findings are robust using a more sophisticated measure of cost efficiency that considers a larger number of cost and output components of a bank's financial statement, in addition to off-balance sheet activities, bank capital, and risk exposure. Given that large banks face a more substantial regulatory burden and that our efficiency measure is more comprehensive, the alternative hypothesis that α_2 is negative and significant is also feasible.

In addition to the log of total assets, we investigate alternative models using categorical variables for banks above certain size thresholds ($10 billion and $50 billion) due to the stricter regulatory restrictions, risk-management oversight, and stress tests (Board of Governors of the Federal Reserve System, 2012). We define a bank to be above \$10 billion or \$50 billion in assets pre-Dodd-Frank Act if it held this amount of assets in its balance sheet during every quarter in the six years before this regulation was implemented. Similarly, we define a bank as targeted by this regulation if its total assets exceed the regulatory size threshold during every period post-2010. This definition ensures that we do not consider banks above such size threshold for a single year as part of the targeted banks. [6]

Moreover, in our alternative specification, the vector $Size_{it}$ also includes a dummy for medium-sized banks to evaluate how the gap in cost efficiency between large and medium-sized banks changed relative to small banks. Banks are classified as medium-sized if they have a minimum of \$100 million in assets during the whole sample but did not qualify as a targeted bank. The use of this threshold to identify medium-sized banks is motivated by the definition of small banks from Dolar and Dale (2020). Given that some may argue that the threshold of \$100 million is too low to identify medium-sized banks, we also produce results increasing the minimum threshold to \$1 billion in assets motivated by the FDIC requiring banks above such size threshold to report a significant number of additional items from their balance sheets and income statements.[7] Hence, this alternative specification classifies medium-sized banks based on the greater regulatory oversight they face relative to smaller banks. This robustness check to classify medium-sized banks can be found in the Appendix.

The vector X_{it} includes variables that control for differences in bank liquidity, ownership structure, risk, bank office specialization in online services, age, regulator, and geographical expansion. We include a variable for bank liquidity since it can impact the cost of bank funding (Gorton and Metrick, 2012) and asset valuation (Pasiouras et al., 2009). Liquidity defines the ability of a bank to meet its short-term financial obligations as it represents cash and marketable securities relative to bank size.[8] In addition, variables indicating bank ownership structure and the standard deviation of bank returns are included to control for risk-taking behavior. Goetz et al. (2016) reports that bank ownership is correlated with differences in risk-taking behavior. The inclusion of the standard deviation of a bank's return on assets is based on the hypothesis that poor bank management can be associated with poor ability to minimize expenditures (Berger and Mester, 1997).

Bank specialization also arises as a variable associated with differences in efficiency among banks. Given the growth of online banking services since the early 2000s, an empirical contribution of this study is the evaluation

[6]We also run sensitivity tests using different specifications to determine targeted banks, such as the average asset size over the sample period being above the size threshold. The qualitative results reported in section 5.2.2 are robust and can be presented upon request.

[7]According to the forms for the Consolidated Reports of Condition and Income for a Bank with Domestic and Foreign Offices (FFIEC 031), in addition to the information all banks report to regulators, banks with assets greater than \$1 billion must also report additional information on their income from the sale and servicing of mutual funds and annuities in domestic offices, components of service charges on deposit accounts in domestic offices, disaggregated data on the allowance for loan and lease losses, securities held-to-maturity and available-for-sale, information on trading assets and liabilities, trading assets and liabilities, deposit liabilities, derivatives and off-balance-sheet items, data for deposit insurance and FICO assessments, 1–4 family residential mortgage banking activities, and service, securitization, and asset sales activities. For more information, visit the Reports section on the FFIEC webpage (https://www.ffiec.gov/ffiec_report_forms.htm).

[8]This measurement is defined as in Shim (2019).

of the relationship between a proxy for bank office specialization in online banking services and cost efficiency. We argue that banks with more offices specialized in online services have a different cost structure related to expenditures on personnel and infrastructure than traditional brick-and-mortar offices. To capture specialization in online banking services, a variable indicating the share of a bank's branches specialized in cyber services is included in the vector of bank characteristics. Our exploration complements Cyree et al. (2009), who report that internet-primary banks are more profit-efficient than their counterparts.

The hypothesis that older banks are more efficient since production involves "learn by doing" motivates the inclusion of bank age in our regression model (Mester, 1996). We include age as a categorical variable rather than a continuous variable due to data limitations in the Call Report data on the date a bank was established. We use the first quarter a bank is present in the data as its opening date, and given that some banks were established before 1976 (our first data point in the raw data), banks older than 30 years old are classified as 30+ years.[9] In addition, given that the regulatory regimes imposed by different regulatory institutions are not homogeneous (Berger and Mester, 1997), we also evaluate which regulatory institution (FDIC, Federal Reserve - FED, or Office of Comptroller of Currency - OCC) is associated with higher bank cost efficiency.

Lastly, the relevance of banking market characteristics on cost efficiency also deserves attention. Rose (1996) reports that geographic diversification can lower a bank's operating costs but emphasizes that such finding depends on the types of regions banks expand to. McKee and Kagan (2019) also stress that market characteristics (metro vs. rural areas) affect a bank's compliance burden from the Dodd-Frank Act. Motivated by these results, we include variables for bank geographical expansion and customer base characteristics in our analysis. For bank expansion, we use a multi-state dummy equal to one for all banks operating in more than one state during at least one point in our sample. Median county household income and population size are included to control for differences in the demand for banking services.

We use county rather than state market characteristics so that we can capture differences in customer characteristics in rural and metropolitan areas within a state. For instance, two banks could be operating in the same state, but one could be operating in less populated and lower-income areas (likely to be rural areas) while the other could be operating in metropolitan areas, which are more populated and have higher-income households. These differences in demand for banking services can affect bank liability and asset composition, thus influencing their ability to minimize costs. For banks operating in more than one county, we create a deposit-weighted average of market characteristics, in which each county receives a weight based on the bank's share of total deposits located

[9]Despite the arbitrary selection of the age bins used in the regression, our qualitative results for the relationship between age and cost efficiency are robust to different age groupings. These results can be provided upon request.

in each county it operates in.[10]

Table 3 reports the definition and descriptive statistics of the cost-efficiency correlates included in the empirical investigation conducted using Equation 5.

Table 3: Descriptive Statistics of Banking Cost Efficiency Correlates

	Pre-Dodd-Frank Act		Post-Dodd-Frank Act	
	Mean	Std. Dev.	Mean	Std. Dev.
$\bar{X}_i$: *Banking Characteristics*				
Size: Assets (in billions)	1.382	25.190	2.070	37.460
Size: \$100 mi $\leq$ Assets $<$ \$10 bi	0.485	0.500	0.627	0.484
Size: Assets $\geq$ 10 bi	0.012	0.109	0.016	0.125
Size: \$100 mi $\leq$ Assets $<$ \$50 bi	0.495	0.500	0.639	0.480
Size: Assets $\geq$ \$50 bi	0.004	0.063	0.005	0.071
Liquidity relative to total assets	0.231	0.140	0.295	0.157
Owner: Bank holding company	0.785	0.397	0.743	0.429
ROA: Standard deviation	0.009	0.016	0.005	0.010
Share of cyber offices	0.002	0.027	0.003	0.037
Age: $\leq$ 10yrs old	0.213	0.410	0.185	0.389
Age: 10 - 20 yrs old	0.090	0.286	0.114	0.317
Age: 20 - 30 yrs old	0.108	0.310	0.071	0.257
Age: $>$ 30 yrs old	0.589	0.492	0.630	0.483
Regulator: FDIC	0.665	0.467	0.633	0.476
Regulator: FED	0.115	0.313	0.123	0.320
Regulator: OCC	0.220	0.410	0.244	0.423
Multi-state	0.062	0.229	0.096	0.285
$\bar{G}_i$: *Regional Characteristics*				
Weighted county population (in millions)	0.440	1.132	0.408	1.076
Weighted county median real income per capita (in 1000s)	55.519	13.526	54.912	13.039

5.2.2 Tobit Regression Results

The results of our empirical investigation are reported in Table 4. They confirm the findings that larger banks tend to be more cost-efficient (Sapci and Miles, 2019) but show that this efficiency gap decreased after the implementation of the Dodd-Frank Act. This is illustrated by the positive coefficient associated with the log of a bank's total assets and the negative coefficient from the interaction term between *DF* and bank size in Column (1). Given that the negative coefficient in Column (3) from the interaction term between *DF* and banks above \$50 billion in assets is over two and a half times the magnitude of the coefficient with the interaction term with banks with at least \$10 billion reported in Column (2), our analysis implies that the decrease in the gap in bank performance is associated with greater regulatory oversight.

[10] As a robustness check, we also run results using state-level controls for income and population. We find that state-level characteristics are not as statistically significant in predicting bank performance for community banks as for regression analyses including all banks. We argue this is due to the relative local nature of community banks since state-level variables are too broad to capture the demand for financial services of banks operating in a small part of the state. These results can be provided upon request.

Even though small banks tend to suffer a more significant change in noninterest expense (Hogan and Burns, 2019), we show that a more comprehensive cost efficiency measurement, which considers environmental risk factors and asset and liability compositions, shows that larger banks' ability to minimize costs was more affected. Nonetheless, despite this regulation's negative effect on larger banks' cost efficiency, they remain, on average, more cost-efficient. We report that the gap in performance between small banks and banks with a minimum of $10 and $50 billion in assets decreased by 35.69 percent and by 55.52 percent, respectively. We argue this is due to the greater reporting requirements, additional stress tests, and stricter risk management requirements they face.

In Column (4), we investigate the impact of the Dodd-Frank Act on a more homogeneous group of banks called community banks that play an essential role in providing loans to small businesses and rural communities.[11] We find that investigating banks operating in smaller geographical areas, which improves controls for market characteristics, produces robust results about how this new regulation decreased the magnitude of the positive correlation between bank size and efficiency. Given that, by definition, community banks tend to be smaller than other banks, the α_2 from Column (4) being smaller in absolute terms than the α_2 from Column (1) emphasizes how including targeted banks affects the change in the gap in efficiency due to economies of scale. The remaining explanatory variables have fairly similar relationships with cost efficiency. The findings for this homogeneous sample of banks indicate that our analyses are robust to concerns about biased results due to the presence of bank heterogeneity in lending strategy (Cyree et al., 2020).

Next, we discuss the relationship between bank efficiency with liquidity and risk-taking behavior. Similar to Pasiouras et al. (2009), our results indicate that higher bank liquidity is negatively associated with banking cost efficiency across banks.[12] Moreover, the coefficients associated with bank risk-taking behavior imply that banks willing to take higher risks tend to be less cost-efficient relative to their counterparts. This negative association between risk-taking behavior and cost efficiency highlights the connection between cost efficiency and the probability of bank failure, as banks investing in riskier assets were more likely to fail during the Great Recession (DeYoung and Torna, 2013).

[11] Recall that the definition of community banks is in Section 3.

[12] Given that the implementation of nontraditional monetary policy tools used by the Federal Reserve during the Great Recession increased liquidity in the banking system (Egly et al., 2016), we also run a robustness check including an interaction term between *DF* and bank liquidity in our regression model. This additional control does not alter the main results presented in this study; rather, it only impacts the magnitude of the relationship between liquidity and efficiency as such interaction term is positive and statistically significant but smaller in magnitude than the negative coefficient associated with bank liquidity in Table 4. These results can be presented upon request.

Table 4: The Potential Determinants of the Cost Efficiency of U.S. Banks

	All Banks			Community Banks
	(1)	(2)	(3)	(4)
Size: Assets (in log units)	0.0264***			0.0222***
	(0.00146)			(0.00144)
Size: \$100 mi $\leq$ Assets $<$ \$10 bi		0.0310***		
		(0.00280)		
Size: \$100 mi $\leq$ Assets $<$ \$50 bi			0.0350***	
			(0.00280)	
Size: Assets $\geq$ \$10 bi		0.174***		
		(0.0242)		
Size: Assets $\geq$ \$50 bi			0.290***	
			(0.0434)	
Post-DF	0.0190	-0.0435***	-0.0430***	0.0101
	(0.0173)	(0.00266)	(0.00259)	(0.0173)
Post-DF x Assets (in log units)	-0.00602***			-0.00499***
	(0.00144)			(0.00144)
Post-DF $\times$ (\$100 mi $\leq$ Assets $<$ \$10 bi)		-0.0123***		
		(0.00333)		
Post-DF $\times$ (\$100 mi $\leq$ Assets $<$ \$50 bi)			-0.0139***	
			(0.00331)	
Post-DF $\times$ (Assets $\geq$ \$10 bi)		-0.0621**		
		(0.0253)		
Post-DF $\times$ (Assets $\geq$ \$50 bi)			-0.161***	
			(0.0448)	
Liquidity factor	-0.156***	-0.168***	-0.167***	-0.163***
	(0.0119)	(0.0119)	(0.0119)	(0.0119)
Owner: Bank holding company	-0.0535***	-0.0468***	-0.0472***	-0.0506***
	(0.00413)	(0.00416)	(0.00416)	(0.00421)
ROA: Standard deviation (%)	-0.252*	-0.298**	-0.302**	-0.616***
	(0.134)	(0.136)	(0.137)	(0.129)
Age: $\leq$ 10yrs old	0.0653***	0.0643***	0.0644***	0.0646***
	(0.00412)	(0.00418)	(0.00418)	(0.00420)
Age: 10 - 20 yrs old	0.0283***	0.0293***	0.0286***	0.0264***
	(0.00481)	(0.00490)	(0.00487)	(0.00507)
Age: 20 - 30 yrs old	-0.00184	-0.00146	-0.00126	-0.00461
	(0.00486)	(0.00494)	(0.00494)	(0.00503)
Share of cyber offices	0.105	0.144**	0.143**	0.120
	(0.0676)	(0.0664)	(0.0658)	(0.0994)
Regulator: FDIC	0.0283***	0.0255***	0.0252***	0.0288***
	(0.00318)	(0.00321)	(0.00320)	(0.00322)
Regulator: FED	0.0156***	0.0153***	0.0147***	0.0200***
	(0.00435)	(0.00441)	(0.00442)	(0.00447)
Multi-state	-0.0372***	-0.0108**	-0.00834*	-0.0415***
	(0.00525)	(0.00504)	(0.00498)	(0.00528)
Weighted county median income (in log units)	0.0961***	0.106***	0.107***	0.0945***
	(0.00687)	(0.00697)	(0.00697)	(0.00705)
Weighted county population (in log units)	0.00594***	0.00860***	0.00855***	0.00482***
	(0.00101)	(0.00102)	(0.00102)	(0.00107)
Constant	-0.944***	-0.785***	-0.793***	-0.866***
	(0.0705)	(0.0713)	(0.0713)	(0.0723)
σ	0.0164	0.0168	0.0168	0.0149
	(0.000405)	(0.000414)	(0.000413)	(0.000399)
Log Likelihood	9452.1	9260.3	9272.5	9211.6
Number of observations	15491	15491	15491	13818

1 Standard errors in parentheses and clustered at the bank level.

2 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Our results imply that in addition to internet-specialized banks experiencing greater bank profitability (Cyree et al., 2009), having a business model that has a larger share of offices specialized in cyber services is only linked with differences in cost efficiency in regressions including non-community banks. We argue this positive link can arise due to the tendency of cyber branches to employ labor (e.g., computer engineers, cyber security officers, among others) that, despite being more expensive, serve a broader customer base online. In contrast, traditional brick-and-mortar office employees (e.g., cashiers) serve a more limited number of in-person customers daily. The lower labor-expenditure-to-customer ratio of banks with a higher share of cyber offices is a possible explanation for this positive association. We claim the link between these variables is weak since the coefficient for cyber office specialization is not statistically different from zero in the regression models using a continuous variable for bank size.

Interestingly, the results for our age coefficients contradict Mester's hypothesis and suggest that young banks are, on average, more efficient. However, we find that the ability of younger banks to be more efficient relative to those open for over 30 years tends to diminish as a bank gets older. Our analysis also shows that banks regulated by the FDIC and the Federal Reserve face regulatory environments that enable them to minimize short-run costs more efficiently relative to banks regulated by the Office of Comptroller of the Currency (OCC). Given that the relationship between regulator and efficiency is not robust to the results from Berger and Mester (1997), this research points to how regulatory changes promoted by different regulators since the 1990s are associated with changes in bank performance. Investigating differences in regulatory frameworks imposed by these regulators can be a fruitful area for future research.

Lastly, our results suggest that bank geographical expansion is negatively associated with higher efficiency. This result goes against the intuition from Rose (1996), who report that geographic diversification can lower a bank's operating costs. Our results indicate the presence of efficiency loss for crossing state borders. A possible explanation is the higher administrative costs of managing service provision across multiple states. Regarding customer characteristics, we report a positive relationship between a stronger demand for banking services (more populated or higher income areas) and their incentive and ability to minimize expenditures. Our findings emphasize the relevance of considering customer characteristics to assess differences in bank performance.

6 Conclusion

This study estimates and provides a descriptive analysis of the cost efficiency of U.S. banks pre- and post-implementation of the Dodd-Frank Act. We focus on this regulatory change due to the magnitude of the number of regulatory restrictions it imposed on U.S. banks, particularly large banks. The exploration of cost efficiency is motivated by studies that report this regulation changed the cost structure of U.S. banks (Hogan and Burns, 2019; Dolar and Dale, 2020). To the best of our knowledge, this is the first study to evaluate the heterogeneous impact of the Dodd-Frank Act on bank cost efficiency on banks facing greater regulatory oversight using a comprehensive measure of cost efficiency empirically linked with the probability of bank failure during a financial crisis (Assaf et al., 2019).

Our empirical analysis documents a positive relationship between bank size and cost efficiency, which explains the lower average cost efficiency reported for the sub-sample with only community banks in Table 2. Nonetheless, despite previous literature showing that smaller banks experienced a higher expenditure increase due to this regulatory change, we uncover that banks above the size thresholds that increase the regulatory restrictions imposed on them experienced a greater decrease in their ability to minimize costs. We argue that these differences in results are due to differences in cost efficiency measurements explored. For instance, rather than using different types of expenses to assets ratios, we use a more sophisticated measure for cost performance that considers interest and noninterest input prices, asset composition, equity, off-balance sheet activities, and market risk exposure.

The two-step approach used in our empirical investigation of the correlates of cost efficiency complements Akhigbe and McNulty (2005), who use a similar approach to investigate variables relevant to bank profit efficiency. Our results imply that one of the indirect effects of the Dodd-Frank Act is a reduction in cost-efficiency advantages due to economies of scale. This reduction in bank efficiency is notably more substantial for banks facing the strictest regulatory restrictions and risk management oversight. Even though banks experiencing this stronger regulatory oversight represent a small share of all banks, they deserve special attention as they have held around 60 and 70 percent of all U.S. bank deposits pre- and post-implementation of this law, respectively. Nonetheless, despite this downward pressure on the gap in bank efficiency for larger banks, these larger banks remain, on average, more cost-efficient relative to their counterparts. In addition to showing that banks with a higher share of offices specializing in online services tend to experience higher cost efficiency, our results also highlight the importance of bank age, ownership structure, risk-taking behavior, regulator, and market characteristics to their ability to minimize costs. We leave the analysis of the overall net benefit of this regulation to future research as it goes beyond the scope of this paper.

Since a higher regulatory burden tends to lower banks' cost efficiency and makes them more prone to failure during a financial crisis, regulators must carefully supervise targeted banks. Upon the next financial crisis, research should re-evaluate if the Dodd-Frank Act altered the link between cost efficiency and its ability to forecast bank failures. In addition, in 2019, the size threshold for facing stricter regulatory restrictions from the Dodd-Frank Act increased from \$50 billion to \$250 billion in assets; hence, future research should investigate the impact of altering the size threshold for stricter regulatory oversight on bank risk-taking behavior. Lastly, another fruitful area of research is the evaluation of how pandemic relief policies affected the cost efficiency of U.S. banks. However, an extended period after these policies were implemented is required to apply the methodology used in this study.

7 Statements and Declarations

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A Appendix

Table 5: The Potential Determinants of the Cost Efficiency of U.S. Banks: Size Sensitivity Tests

	All Banks	
	(1)	(2)
Size: \$1 bi $\leq$ Assets $<$ \$10 bi	0.0584***	
	(0.00757)	
Size: \$1 bi $\leq$ Assets $<$ \$50 bi		0.0768***
		(0.00772)
Size: Assets $\geq$ \$10 bi	0.162***	
	(0.0242)	
Size: Assets $\geq$ \$50 bi		0.282***
		(0.0437)
Post-DF	-0.0465***	-0.0460***
	(0.00165)	(0.00163)
Post-DF $\times$ (\$1 bi $\leq$ Assets $<$ \$10 bi)	-0.0218***	
	(0.00810)	
Post-DF $\times$ (\$1 bi $\leq$ Assets $<$ \$50 bi)		-0.0300***
		(0.00866)
Post-DF $\times$ (Assets $\geq$ \$10 bi)	-0.0591**	
	(0.0252)	
Post-DF $\times$ (Assets $\geq$ \$50 bi)		-0.158***
		(0.0449)
Constant	-0.783***	-0.773***
	(0.0717)	(0.0717)
σ	0.0169	0.0168
	(0.000413)	(0.000410)
Bank controls	Yes	Yes
Market controls	Yes	Yes
Log Likelihood	9240.6	9279.2
Number of observations	15491	15491

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$