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Frontier efficiency, capital structure, and portfolio risk: An empirical analysis of U.S. banks

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Abstract Firm' ability to effectively allocate capital and manage risks is the essence of their production and performance. This study investigated the relationship between capital structure, portfolio risk levels and firm performance using a large sample of U.S. banks from 2001 to 2016. Stochastic frontier analysis (SFA) was used to construct a frontier to measure the firm's cost efficiency as a proxy for firm performance. We further look at their relationship by dividing the sample into different size and ownership classes, as well as the most and least efficient banks. The empirical evidence suggests that more efficient banks increase capital holdings and take on greater credit risk while reducing risk-weighted assets. Moreover, it appears that increasing the capital buffer impacts risk-taking by banks depending on their level of cost efficiency, which is a placeholder for how productive their intermediation services are performed. An additional finding, is that the direction of the relationship between risk-taking and capital buffers differs depending on what measure of risk is used.

Introduction

The measurement of firm performance is central to management research. Traditional techniques such as financial ratio analysis summarizing firm performance in a single statistic are widely used. Despite the appealing simplicity, this approach have been heavily criticized as it fails to control for product mix or input prices (Berger et al., 1993), is susceptible to changes of external prices that are beyond the control of the management (De Young, 1997), and also the comparison of the firm-specific performance without peer groups is meaningless.

The structural approach on firm performance focuses especially on the *frontier efficiency*, a concept motivated by the theory of production that firms cannot operate above the ideal ''frontier'' and the deviations from the ''frontier'' represent the individual inefficiencies. The frontier efficiency measures how efficient the firm is compared to the ''best practice'' firm in the market. Frontier efficiency

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models have wide applications in many industries across the world, such as evaluating the outcomes of market reforms, and establishing performance benchmarks.

Efficiency study is specially relevant in the financial sector. The 2007 global financial crisis had a significant impact on the performance of financial institutions and the stability in the financial system. The crisis not only revealed that the existing regulatory frameworks were still inadequate for preventing financial institutions from taking excessive risks, but also highlighted the importance of the interdependence and spillover effects within the financial markets. Therefore, from a management perspective, these events have prompted a need in understanding the key components of firm technology and production to better prevent risks and improve performance.

Literature recognizes that a firm's choices of risk-taking and capital allocation influence its production decisions, and so, in turn, affects its cost and profitability. Hughes et al. (1995) link risk-taking and firm's operational efficiency together and argue that higher loan quality is associated with greater inefficiencies. Kwan and Eisenbeis (1997) link firm risk, capitalization and measured inefficiencies in a simultaneous equation framework. Their study confirms the belief that these three variables are jointly determined. Taken together, empirical literature on banking business practices imply that capital, risk and efficiency are all related.

Understanding the relationship between capital structure, efficiency and risk decisions is therefore fundamental in management, and the underlying mechanisms should be fully understood by managers to improve firm performance and prevent any hazardous behavior. The aim of the paper is to gain a better understanding of the effects of capital structure, risk and efficiency among each other. To reach this objective, we use empirical data in a sector of great interest, the U.S. banking sector. The sampling period includes banks that report their balance sheet data according to both the original Basel I Accord and the Basel II revisions (effective from 2007 in the U.S.), and up to the most available date 2016-Q3. More precisely, this paper addresses the following questions: How does a firm's risk-taking, capital and efficiency relate to each other? To what extent are firm's risk-taking behavior and efficiency levels sensitive to capital regulation? Do firms behave differently depending on the size, efficiency or ownership classes?

This study makes several contributions to the discussion on capital, risk and efficiency and has important implications. First, this analysis provides the the first empirical investigation, which links capital regulation on bank risk taking, capital buffer and efficiency while accounting for the simultaneous relationship between them. Second, this study employs a significantly larger and more recent data set compared to previous studies that used data only up to 2010. In addition, the findings of this study will offer useful insights for regulators and managers in the rapidly changing institutional environment.

This paper is organized as follows. We begin by introducing the fundamentals of the frontier efficiency methods. We then review the hypothesis between capital, risk and efficiency. This is followed by our model and estimation strategies. We then illustrate our methodologies using panel data on U.S. banks and present our findings.

Frontier efficiency: conceptual background

The basic idea of efficiency analysis is to measure firm's performance of the extent to which inputs are well used for outputs (products or services.) The non-structural approach to measure efficiency uses simple financial ratios from accounting statements such as *return-on-equity* or the ratio of operating costs to total assets.

The structural approach relies on theoretical models of production and the concept of optimization. Generally, there are two approaches to measure the *frontier efficiency*: the parametric and the non-parametric approach. Parametric methods, like Stochastic Frontier Analysis (SFA), Thick Frontier Approach (TFA) and Distribution Free Approach (DFA), are used to estimate a pre-specified functional form and inefficiency is modeled as an additional stochastic term. On the other hand, non-parametric methods, including Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH) approach, use linear programming to calculate an efficient deterministic frontier against which units are compared.

Stochastic frontier analysis (SFA)

The most widely implemented technique is stochastic frontier analysis (SFA) proposed by Aigner et al. (1977), Meeusen and Van den Broeck (1977). SFA is often referred to as a composed error model where one part represents statistical noise with symmetric distribution and the other part, representing inefficiency, follows a particular one-sided distribution. The availability of a panel data enables the use of standard models of fixed and random effects without the need to make any distributional assumption for the inefficiency term (Schmidt and Sickles, 1984). This is the Distribution Free Approach (DFA). The model has the general form:

$$\begin{aligned} y_{it} &= \alpha + f(x_{it};\beta) + u_i + v_{it}, \\ i &= 1, 2, \ldots N, t = 1, 2, \ldots T_i. \end{aligned} \tag{1}$$

where x_{it} is a vector of input variables, y_{it} is the output variable, $f(x_{it};\beta)$ is a log-linear production function (e.g. Cobb-Douglas, translog or fourier flexible form) and α is the frontier intercept. v_{it} is the statistical noise, and is assumed to be independently and identically distributed, and u_i is the one-sided inefficiency term that represents technical inefficiency of firm i. u_i is assumed to have half-normal, truncated normal, exponential, or gamma distribution.

The fundamental idea of stochastic frontier technical efficiency can be formalized as the ratio of realized output, given a specific set of inputs, to maximum attainable output:

$$TE_{it} = \frac{y_{it}}{y_{it}^*} = \frac{f(x_{it};\beta)e^{-u_{it}}e^{v_{it}}}{f(x_{it};\beta)e^{v_{it}}} = e^{-u_{it}} \in (0, 1]$$

with y_{it}* is the maximum attainable output for unit i given x_{it}.

Later, Cornwell et al. (1990) (CSS) extended the standard panel data stochastic frontier model in (1) to allow for heterogeneity in slopes as well as intercepts. The intercept is specified as:

$$\alpha_{it} = \delta_i W_t = \delta_{i1} + \delta_{i2} t + \delta_{i3} t^2$$

where the parameters δ_{i1}, δ_{i2}, δ_{i3} are firm specific and t is the time trend variable.

Following a slightly different strategy, Lee and Schmidt (1993) specifies u_{it} as the form of $g(t)u_i$ in which

$$g(t)u_i = (\sum_{t=1}^{T} \beta_t d_t) u_i$$

where d_t is a time dummy variable and one of the coefficients is set equal to one.

Numerous similarly motivated specifications have been proposed for u_{it}. Two that have been proved useful in applications are Kumbhakar (1990)'s model,

$$g(t) = \left(1 + \exp\left(\eta_1 t + \eta_2 t^2\right)\right)^{-1}.$$

and Battese and Coelli (1992)'s ''time decay model'',

$$g(t) = \exp[-\eta(t - T_i)].$$

where T_i is the last period in the i_{th} panel, and η is the decay parameter. The decay parameter gives information on the evolution of the inefficiency. When $\eta > 0$, the degree of inefficiency decreases over time; when $\eta < 0$, the degree of inefficiency increases over time. If η tends to 0, then the time-varying decay model reduces to a time-invariant model.

Non-parametric approach

Data envelopment analysis (DEA), introduced by Charnes et al. (1979), provides a nonparametric methodology to evaluate the relative efficiency of each of a set of comparable decision making units (DMUs) relative to one another. DEA assumes that there is a frontier technology (in the same spirit as the stochastic frontier production model) that can be described by a piece-wise linear convex hull that envelopes the observed outcomes. In contrast to SFA, DEA is purely deterministic and creates virtual units that serve as benchmarks for measuring DMUs' comparative efficiency. Free disposal hull (FDH) analysis is similar to DEA, but relaxes the convexity assumption of DEA models. Therefore, compared to DEA frontier, data is enveloped more tightly in the FDH, which has a staircase shape.

Main hypothesis between capital, risk and efficiency

The manager's role is vital in making decisions about their capital structure and the amount of risk to assume. Modern banking theory emphasizes managers' contrasting incentives. On the one hand, managers are obliged to fulfill shareholders' objectives especially to maximize the value of equity shares. On the other hand, managers are restrained their attempts to take excessive risk by means of a restrictive regulatory system. The prevalence of a minimum capital requirement is primarily based on the assumption that banks are prone to engage in moral hazard behavior. The moral hazard hypothesis is the classical problem of excessive risk-taking when another party is bearing part of the risk and cannot easily charge for that risk. Due to asymmetric information and a fixed-rate deposit insurance scheme, the theory of moral hazard predicts that banks with low levels of capital have incentives to increase risk-taking in order to exploit the value of their deposit insurance (Kane, 1995). The moral hazard problem is particularly relevant when banks have high leverage and large assets. According to the *too-big-to-fail* argument, large banks, knowing that they are so systemically important and connected that their failure would be disastrous to the economy, might count on a public bailout in case of financial distress. Thus, they have incentives to take excessive risks and exploit the implicit government guarantee. In addition, the moral hazard hypothesis predicts that inefficiency is positively related to higher risks because inefficient banks are more likely to extract larger deposit insurance subsidies from the FDIC to offset part of their operating inefficiencies (Kwan and Eisenbeis, 1996).

With regard to the relationship between cost efficiency and risks, Berger and DeYoung (1997) outline and test the ''bad luck'', ''bad management'', and ''skimping'' hypotheses using Granger causality test. Under the bad luck hypothesis, external exogenous events lead to increases in problem loans for the banks. The increases in risk incur additional costs and managerial efforts. Thus cost efficiency is expected to fall after the increase in problem loans. Under the bad management hypothesis, managers fail to control costs, resulting in a low cost efficiency, and they also perform poorly at loan underwriting and monitoring. These underwriting and monitoring problems eventually lead to high numbers of nonperforming loans as borrowers fall behind in their loan repayments. Therefore, the bad management hypothesis implies that lower cost efficiency leads to an increase in problem loans. On the other hand, the skimping hypothesis implies a positive Granger-causation from measured efficiency to problem loans. Under the skimping hypothesis, banks skimp on the resources devoted to underwriting and monitoring loans, reducing operating costs and increasing cost efficiency in the short run. But in the long run, nonperforming loans increase as poorly monitored borrowers fall behind in loan repayments.

Model and identification strategy

Measuring efficiency

How one measures performance depends on whether one views the firm as cost minimizing, profit maximizing or managerial utility maximizing. The cost efficiency is the most widely used efficiency criterion in the literature, and measures the distance of a firm's cost relative to the cost of the best practice firm when both of them produce the same output under the same conditions. A firm's production function uses labor and physical capital to attract deposits. The deposits are used to fund loans and other earning assets. We specify inputs and outputs according to the intermediation model (Sealey and Lindley, 1977).

Following Altunbas et al. (2007), we specify a cost frontier model with two-output three-input, and a translog specification of the cost function:

$$\begin{aligned}\ln TC &= \beta_0 + \gamma t + 0.5\gamma t^2 \\ &+\sum_{h=1}^{3}(\alpha_h+\theta_h t)\ln w_h + \sum_{j=1}^{2}(\beta_j + c_h t)\ln y_j \\ &+0.5(\sum_{j=1}^{2}\sum_{k=1}^{2}\beta_{jk}\ln y_j \ln y_k + \sum_{h=1}^{3}\sum_{m=1}^{3}\lambda_{hm}\ln w_h \ln w_m) \\ &+\sum_{i=1}^{2}\sum_{m=1}^{3}\rho_{im}\ln y_i \ln w_m - u + v\end{aligned} \tag{2}$$

where TC represents the total cost, y are outputs, w are input prices, and t is a time trend to account for technological change, using both linear and quadratic terms. Inputs are borrowed funds, labor, and capital. Outputs are securities and loans. The inclusion of quadratic time trend and time interaction with outputs and input prices enables the measurement of time-dependent effects in costs, such as the pure technical change and non-neutral technological shifts of the cost frontier. The term v is a random error that incorporates both measurement error and luck. u measures the distance of an individual bank to the efficient cost frontier and represents the bank's inefficiency level. A description of input and output variables are shown in Table 4.1.

Eq. (2) is estimated using several methods. We first estimate cost efficiency using Battese and Coelli (1992) time-decay model with time-varying efficiency which is the model of choice in many applications. We then estimate firms' relative efficiency follow (Cornwell et al., 1990) model using within transformation. Since CSS estimators are vulnerable to outliers and measurement error, we also incorporate a TFA and order-α type of estimation technique with CSS within estimator to estimate average efficiency of each quartile and compare across groups. Within the banking literature, size has often been found to be a key factor driving variations in efficiency across banks. It is interesting to note that there is no consensus in previous empirical studies about the relationship between bank size and banking efficiency. The modified estimations of relative cost efficiency are as follows:

1. We first sort the data of banks by asset size, from small to large, and the sorted sample is divided into quartiles. Firms in the first quartile are the smallest firms and are assumed to be the most cost efficient group of firms.
2. Use a procedure similar to Cornwell et al. (1990) to get the inefficiency and efficiency scores for each quartile separately.
3. Choose $[100-\alpha]$th(where α=90) percentile among banks in each quartile, i.e. trim 10% of the super efficient banks from the sample.
4. Repeat Step 2 to get relative inefficiency and efficiency scores of each bank in each quartile.

Modelling framework

Taken all together, these studies and the models on which they are based imply that bank capital, risk and efficiency are simultaneously determined and can be expressed in general terms as follows:

$$\begin{aligned}RISK_{i,t} &= f(Cap_{i,t}, Eff_{i,t}, X_{it}) \\ Cap_{i,t} &= f(Risk_{i,t}, Eff_{i,t}, X_{it}) \\ Eff_{i,t} &= f(Cap_{i,t}, Risk_{i,t}, X_{it})\end{aligned} \tag{3}$$

where X_{it} are bank-specific variables.

Measures of capital and risk

Given the regulatory capital requirements associated with Basel I, II and III, capital ratios are measured in three ways: Tier 1 risk-based ratio, total risk-based ratio and Tier 1 leverage ratio. Tier 1 risk-based capital ratio is the proportion of core capital to risk-weighted assets where core capital basically consists of common stock and disclosed reserves or retained earnings. Tier 2 capital includes revaluation reserves, hybrid capital instruments and subordinated term debt, general loan-loss reserves, and undisclosed reserves. Total risk-based ratio is the percentage of Tier 1 and Tier 2 capital of risk-weighted assets. Tier 1 leverage ratio is the ratio of Tier 1 capital to total assets. The higher the ratio is, the higher the capital adequacy.

The literature suggests a number of alternatives for measuring bank risk. The most popular measures of bank risk

Table 4.1 Input and output description.

Variable	Symbol	Description
Total cost	TC	Interest + non-interest expenses
Outputs		
Total securities	Y1	Securities held to maturity + securities held for sale
Total loans	Y2	Net loans (gross loans − reserve for loan loss provisions)
Inputs prices		
Price of physical capital	W1	Expenditures on premises and fixed assets/premises and fixed assets
Price of labor	W2	Salaries/full-time equivalent employees
Price of borrowed funds	W3	Interest expenses paid on deposits/total deposits

are the ratio of risk-weighted assets to total assets (*RWA*) and the ratio of non-performing loans to total loans (*NPL*). The ratio of risk-weighted assets is the regulatory measure of bank portfolio risk, and was used by Shrieves and Dahl (1992), Jacques and Nigro (1997), Rime (2001), Aggarwal and Jacques (2001), Stolz et al. (2004) and many others. The standardized approach to calculating risk-weighted assets involves multiplying the amount of an asset or exposure by the standardized risk weight associated with that type of asset or exposure. Typically, a high proportion of *RWA* indicates a higher share of riskier assets. Since its inception, risk weighting methodology has been criticized because it can be manipulated (for example, via securitization), *NPL* is thus used as a complementary risk measure as it might contain information on risk differences between banks not caught by *RWA*. Non-performing loans is measured by loans past due 90 days or more and non-accrual loans and reflect the ex-post outcome of lending decisions. Higher values of the *NPL* ratio indicate that banks ex-ante took higher lending risk and, as a result, have accumulated ex-post higher bad loans.

Determinants of capital structure

The optimal capital structure is not observable and typically depends on some set of observable bank-specific variables. We do so as well in our analysis. Loan loss provisions (*LLP*) as a percentage of assets are included as a proxy for asset quality. A higher level of loan loss provisions indicates an expectation of more trouble in the banks' portfolios and a resulting greater need for capital, and thus might capture ex-ante credit risk or expected losses.

The loan-to-deposit ratio (*LTD*) is a commonly used measure for assessing a bank's liquidity. If the ratio is too high, it means that the bank may not have enough liquidity to cover any unforeseen fund requirements, and conversely, if the ratio is too low, the bank may not be earning as much as it otherwise earns.

Size will likely impact a bank's capital ratios, efficiency and level of portfolio risk, because larger banks are inclined to have larger investment opportunity sets and are granted easier access to capital markets. For these reasons, they have been found to hold less capital ratios than their smaller counterparts (Aggarwal and Jacques, 2001). We include the natural log of total assets as the proxy for bank size. Bank profitability is expected to have a positive effect on bank capital if the bank prefers to increase capital through retained earnings. An indicator of profitability is measured by return on assets (*ROA*) and return on equity (*ROE*).

The regulatory pressure variable describes the behavior of banks close to or below the regulatory minimum capital requirements. Capital buffer theory predicts that an institution approaching the regulatory minimum capital ratio may have incentives to boost capital and reduce risk to avoid the regulatory cost triggered by a violation of the capital requirement. We compute the capital buffer as the difference between the total risk-weighted capital ratio and the regulatory minimum of 8%. Consistent with previous work, we use a dummy variable *REG* to signify the degree of regulatory pressure that a bank is under. Since most banks hold a positive capital buffer, we use the 10th percentile of the capital buffer over all observations as the cutoff point. The dummy *REG* is set equal to 1 if the bank's capital buffer is less than the cutoff value and zero otherwise. To test the predictions outlined above, we interact the dummy *REG* with variables of interest. For example, in order to capture differences in the speeds of adjustment of low and high buffer

Table 4.2 Description of variables used in the study.

Variables	Descriptions
Capital:	
Tier 1 risk-based ratio	Core Capital (Tier 1)/ Risk-weighted Assets
Total risk-based ratio	Core Capital (Tier 1)+Tier 2 capital/Risk-weighted Assets
Tier 1 leverage ratio	Core Capital (Tier 1)/Total assets
Risk:	
NPL ratio	Non-performing Loans/Total assets
RWA ratio	Risk-weighted Assets/Total assets
Bank-specific variables:	
Size	The natural logarithm of banks' total assets
ROA	Annual net income/total assets
ROE	Annual net income/total equity
LLP ratio	Loan loss provisions/total assets
Cash ratio	Noninterest-bearing balances, currency, and coin/total assets
Loan-deposit ratio	Total loans/ Total deposits
Buffer	Total risk weighted capital ratio -8%
REG (Regulatory Pressure)	1 if a bank has a capital buffer $\leq$ 10th percentile capital buffer over all observations, and zero otherwise
Macro indicators:	
GDPG	Growth rate of real GDP for the United States
Crisis	1 if year is between 2007 and 2009 and 0 otherwise
Case–Shiller Home Price Index	Growth rate of 20-city composite constant-quality house price indices

Table 5.1 Summary Statistics of the portfolios of U.S. banks.

	Mean	Std. dev.	Min	Max
Panel A: Descriptive statistics of key variables for the full sample period				
Stochastic frontier arguments				
Cost of physical capital	0.20	0.21	0.02	1.97
Cost of labor	35.05	18.46	8.33	102.43
Cost of borrowed funds	0.01	0.01	0.00	0.04
Total securities ($million)	51.19	74.95	0.41	770
Total loans($million)	160.17	212.36	7.61	1726
Total Cost($million)	6.30	8.94	0.25	167
Regression arguments				
Assets($million)	239.4	301.6	9.6	3540
Equity($million)	24.6	32.5	0.7	577
Deposit($million)	196.0	240.2	7.5	2666
Net income ($million)	1.3	2.9	−261.6	109
Return on assets (%)	0.54	0.64	−27.48	9.16
Return on equity (%)	5.32	6.56	−304.34	83.21
Risk weighted assets (%)	68.05	11.80	36.43	95.78
NPL ratio (%)	2.73	2.73	0.00	51.27
Loan loss provision (%)	0.24	0.54	−20.92	44.54
Tier1 capital ratio (%)	15.30	5.38	7.23	43.09
Risk-based capital ratio (%)	16.43	5.37	9.91	43.48
Tier1 leverage ratio (%)	10.02	2.46	6.08	20.64
Capital buffer (%)	8.43	5.37	1.91	35.48

banks, we interact *REG* with the lagged dependent variables Cap_{t-1} and $Risk_{t-1}$. In addition, to assess differences in short term adjustments of capital and risk that depend on the degree of capitalization, we interact the dummy *REG* with $\Delta Risk$ and ΔCap in the capital and risk equations respectively.

Macroeconomic shocks such as a recession and falling housing prices can also affect capital ratios and portfolios of banks. In order to capture the effect of common macroeconomic shocks that may have affected capital, efficiency and risk during the period of study, the annual growth rate of real U.S. GDP and Case–Shiller Home Price Index are included as controls. We also include a dummy variable *Crisis* that takes the value of 1 if the year is 2007, 2008 or 2009. A summary of variable description is presented in Table 4.2 below.

Given the discussion above, Eq. (3) can be written as:

$$\begin{aligned}
\Delta RISK_{i,t} = \quad & \alpha_0 + \alpha_1 \Delta Cap_{i,t} + \alpha_2 Eff_{i,t} + \alpha_3 RISK_{i,t-1} + \alpha_4 X_{i,t} \\
& + \alpha_5 \Delta Macro_t \\
& + \alpha_6 REG_{i,t} \times \Delta Cap_{i,t} + \alpha_7 REG_{i,t} \times Risk_{i,t-1} + v_{i,t} \\
\Delta Cap_{i,t} = \quad & \gamma_0 + \gamma_1 \Delta Risk_{i,t} + \gamma_2 Eff_{i,t} + \gamma_3 Cap_{i,t-1} + \gamma_4 X_{i,t} \\
& + \gamma_5 \Delta Macro_t \\
& + \gamma_6 REG_{i,t} \times \Delta Risk_{i,t} + \gamma_7 REG_{i,t} \times Cap_{i,t-1} + u_{i,t} \\
Eff_{i,t} = \quad & \sigma_0 + \sigma_1 \Delta Risk_{i,t} + \sigma_2 \Delta Cap_{i,t} + \sigma_3 X_{i,t} \\
& + \sigma_4 \Delta Macro_t + w_{i,t}
\end{aligned} \tag{4}$$

Data

All bank-level data is constructed from the Consolidated Report of Condition and Income (referred to as the quarterly Call Reports) provided by the Federal Deposit Insurance Corporation (FDIC). The sample includes all banks in the Call Report covering the period from 2001:Q1 to 2016:Q3. Complete data of period 2001–2010 is available from the website of the Federal Reserve Bank of Chicago[1] and data after 2011 is available from the FFIEC Central Data Repository's Public Data Distribution site (PDD).[2] We also collected data on U.S. Gross Domestic Product (GDP) and Case–Shiller Home Price Index from Federal Reserve Bank of St. Louis. We end up with an unbalanced panel data on 8055 distinct banks, yielding 330,970 bank-quarter observations over the whole sample period.

Tables 5.1 and 5.2 presents a descriptive summary of key variables in the full sample (panel A) and compares the sample mean for 3 periods: pre-crisis, crisis and post-crisis (panel B). All variables are averaged by banks from 2001 to 2016. Fig. 1 shows the time series plots of bank risks, capital ratios, assets, profits, liquidity, and average capital and interest costs for the average bank over 2001–2016.

In general, the majority of banks in the sample have been well capitalized throughout the sample period. The average bank has exceeded the minimum required capital ratio by a comfortable margin. In our sample, the mean capital buffer above capital requirements is 8.43 %. The average Tier 1

[1] https://www.chicagofed.org/banking/financial-institution-reports/commercial-bank-data.

[2] https://cdr.ffiec.gov/public/PWS/DownloadBulkData.aspx.

Table 5.2 Summary statistics of the portfolios of U.S. banks.

	Pre-crisis 2001q1-2007q2	Crisis 2007q3-2009q4	Post-crisis 2010q1-2016q3
Panel B: Sample mean of key variables for pre-crisis, crisis and post-crisis period			
Stochastic frontier arguments			
Cost of physical capital	0.201	0.192	0.192
Cost of labor	30.365	35.505	40.053
Cost of borrowed funds	0.014	0.016	0.004
Total securities ($million)	42.819	46.613	62.849
Total loans ($million)	128.651	171.229	189.787
Total Cost ($million)	5.747	7.702	6.205
Regression arguments			
Assets ($million)	192.100	244.572	289.565
Equity ($million)	18.815	24.544	31.085
Net income ($million)	1.342	0.899	1.451
Deposit ($million)	155.824	196.543	240.498
Return on assets (%)	0.652	0.404	0.477
Return on equity (%)	6.720	3.989	4.440
Risk weighted assets (%)	68.244	71.086	66.302
NPL ratio (%)	2.216	3.328	2.994
Loan loss provision (%)	0.193	0.356	0.246
Loan-deposit ratio (%)	78.125	81.887	74.809
Tier1 capital ratio (%)	14.882	14.573	16.125
Risk-based capital ratio (%)	16.015	15.674	17.276
Tier1 leverage ratio (%)	9.752	9.955	10.354
Capital buffer (%)	8.015	7.674	9.276

capital ratio is 15.26% and the average risk-based capital ratio is 16.43% during 2001–2016. The findings show that banks tend to hold considerable buffer capital.

Comparing average bank portfolios during the pre-crisis, crisis and post-crisis period, it is evident that an average bank was hit hard by the financial turmoil. The average *ROE (ROA)* dropped from its highest level (7%/0.7%) in 2005 to its lowest (2%/0.2%) in 2009. The time trend of capital ratios shows a steady movement until a drop in 2008 and then picked up after 2010. The time series plots of two measures of bank risks show a similar trend. Liquidity here is measured by cash ratio and *LTD*. The average *LTD* ratio increased steadily until the financial crisis hit and reached the peak of almost 100% in 2009, then fell precipitously until 2012 and have been rising again. The high *LTD* during crisis period suggests insufficient liquidity to cover any unforeseen risks. This sharp drop in *LTD* since 2010 could be attributed to the tightened credit management by banks after the financial crisis, the contraction in lending demand due to the sluggishness of the economy, and the measures undertaken by the government to curb excessive lending.

Empirical results

Estimates of bank cost efficiency are reported in Tables 6.2 and 6.1. The results of the two-step GMM estimation for the full sample are reported in Table 6.5. We also did GMM estimation separately for each size and ownership class, as well as the most and least efficient banks. The estimation results for the subsamples are presented in Table A.1–A.3, respectively. Capital ratios here are measured by Tier 1 leverage ratio. We also did additional tests that used two other measures of capital ratios, and none of these cause material changes to the results reported in the tables.

Table 6.1 Efficiency estimates based on the translog cost functions.

Estimated inefficiencies $\hat{u}_{it}$	
Mean	0.508
SD	0.243
Min	0.006
Max	1.290
Estimated cost efficiency $\hat{CE}_{it}$	
Mean	0.619
SD	0.149
Min	0.275
Max	0.994
Observations	330,790

Note: The top and bottom 5% of inefficiencies scores are trimmed to remove the effects of outliers.

Inefficiency estimation

We estimate cost efficiency specifications in Eq. (2) using Battese and Coelli (1992)'s method. Table 6.1 shows average cost inefficiency at U.S. banks to be around 0.508 and mean cost efficiency to be 0.619. That is, given its particular output level and mix, on average, the minimum cost is about 61.9% of the actual cost. Alternatively, if a bank were to use its inputs as efficiently as possible, it could reduce its production cost by roughly 50.8%.

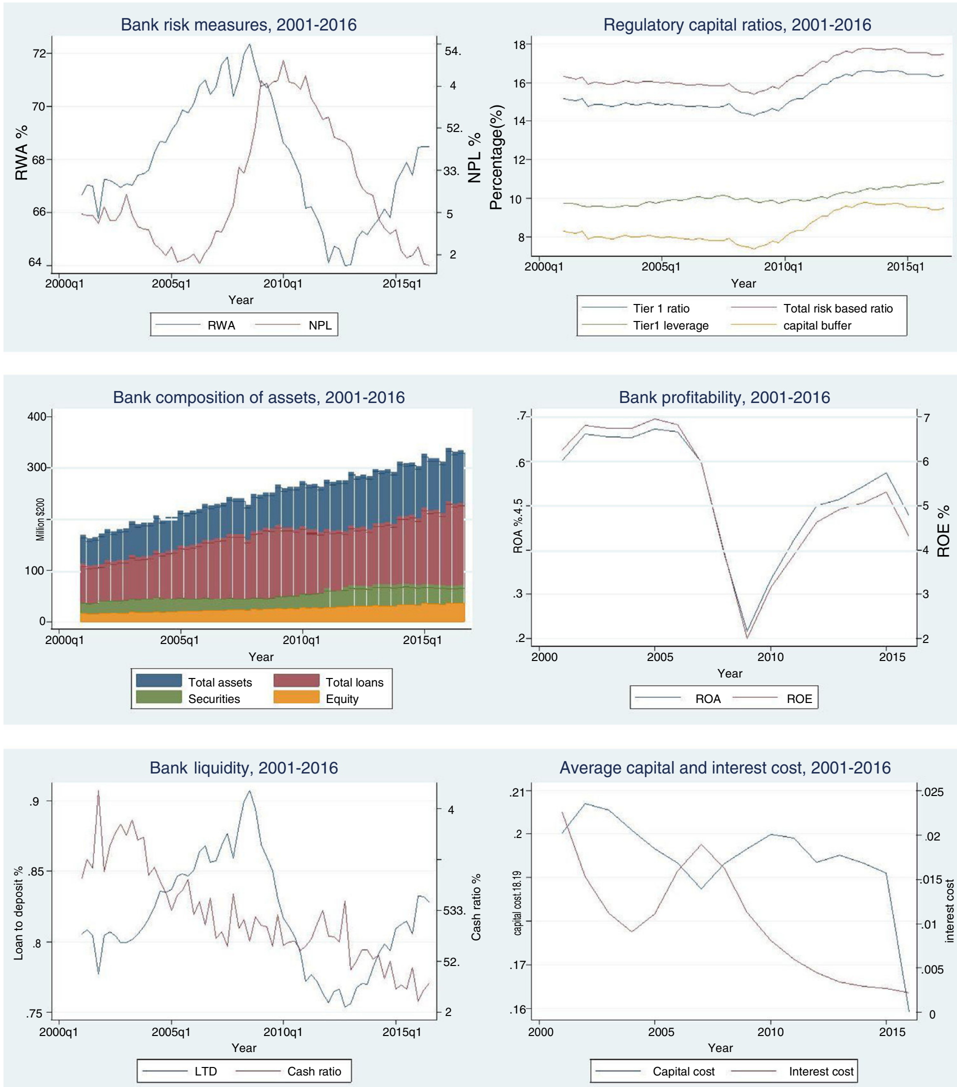

Figure 1 Time series plots of key variables for the pooled sample over 2001–2016.

Table 6.2 Cost efficiency scores by size and type of banks over years.

	Commercial banks	Cooperative banks	Savings banks	Large banks	Small banks	Full sample
2001	0.667	0.740	0.642	0.581	0.668	0.667
2002	0.661	0.734	0.636	0.575	0.662	0.661
2003	0.653	0.729	0.625	0.558	0.655	0.653
2004	0.646	0.718	0.616	0.549	0.648	0.645
2005	0.638	0.712	0.607	0.539	0.640	0.638
2006	0.630	0.703	0.598	0.527	0.633	0.630
2007	0.624	0.684	0.588	0.513	0.626	0.623
2008	0.620	0.680	0.584	0.504	0.623	0.619
2009	0.615	0.671	0.576	0.492	0.619	0.614
2010	0.608	0.665	0.567	0.479	0.612	0.606
2011	0.600	0.651	0.556	0.465	0.604	0.599
2012	0.597	0.650	0.547	0.469	0.601	0.595
2013	0.588	0.648	0.542	0.469	0.592	0.587
2014	0.578	0.646	0.529	0.459	0.583	0.576
2015	0.569	0.642	0.515	0.451	0.574	0.567
2016	0.564	0.639	0.508	0.455	0.569	0.561

Notes: Large banks are banks with assets greater than 1 billion and small banks are banks with assets less than 1 billion.

Table 6.3 Cost efficiency scores over years (banks are divided into quartiles according to their size.)

YEAR	Full sample	Q1	Q2	Q3	Q4
2001	0.5224	0.6565	0.5024	0.3882	0.3026
2002	0.4473	0.5694	0.4403	0.3478	0.2666
2003	0.4161	0.5358	0.4208	0.3309	0.2553
2004	0.4060	0.5281	0.4160	0.3310	0.2536
2005	0.4149	0.5425	0.4327	0.3469	0.2631
2006	0.4772	0.6309	0.5083	0.4059	0.3047
2007	0.4488	0.6016	0.4886	0.3868	0.2904
2008	0.4611	0.6243	0.5163	0.4051	0.2990
2009	0.4394	0.6017	0.5041	0.3907	0.2881
2010	0.4260	0.5886	0.4977	0.3854	0.2822
2011	0.3809	0.5326	0.4525	0.3504	0.2557
2012	0.4220	0.5948	0.5111	0.3948	0.2868
2013	0.4394	0.6198	0.5393	0.4173	0.2996
2014	0.4093	0.5823	0.5138	0.3911	0.2814
2015	0.3968	0.5647	0.5087	0.3833	0.2771
2016	0.3542	0.5044	0.4544	0.3481	0.2502
Total	0.4301	0.5834	0.4805	0.3773	0.2789

Note: Estimated using CSS within estimator.

Table 6.4 Summary statistics for contemporaneous relative efficiency estimates.

Mean efficiency	Quartile 1	Quartile 2	Quartile 3	Quartile 4
2001Q1	0.793	0.653	0.646	0.638
2008Q4	0.749	0.620	0.615	0.608
2016Q3	0.620	0.588	0.578	0.569

Table 6.2 presents the level of cost efficiency for the entire sample and for different ownership and size classes during 2001–2016. Cooperative banks have higher costs efficiency than commercial and savings banks. The results are in line with Altunbas et al. (2003)'s findings, who showed that cooperative banks have higher cost efficiency as compared to the commercial banks. Also, smaller banks are more cost efficient than are the larger banks during all periods.

We also computed relative efficiency scores as outlined in the model section for all banks to assess individual bank performance relative to the expected performance of peer banks; regulators, managers and shareholders, including prospective acquirers, might also find this information useful. The columns labeled ''Q1'', ''Q2'', ''Q3'', and ''Q4'' give the estimated average efficiency levels for the first, second, third and forth size quartiles of banks (Table 6.3).

Specifically, we divided banks into quartiles according to total assets for 3 sample periods: 2001Q1, 2008Q4 and 2016Q3. Table 6.4 shows results for estimation of cost efficiency at these 3 periods and the estimated average efficiency levels for the first, second, third and forth quartiles of banks.

Fig. 2 are scatterplots of averaged efficiency scores computed using the CSS within method for each size quartile at 3 different periods. The analysis shows that cost efficiencies are the highest in the small-sized group, and that the firms with the lowest cost efficiency are largest firms in all 3 periods.

Our results find a significant negative relationship between size and banking efficiency, suggesting that small banks may possess operational advantages that bring about higher cost efficiencies.

GMM results for the full sample

Relationships between capital, risk and efficiency

Table 6.5 shows the GMM fixed effect estimates of risk, capital, and efficiency equation for the full sample using two different measures of risk. Fixed effects are used to account for the possible bank-specific effects and provide consistent estimates. The Hansen statistics are also presented. The non-significance of the Hansen J-statistics indicates that the null hypothesis of valid instruments cannot be rejected for each model, confirming the validity of the instruments used.

The empirical results show that there is a strong positive two-way relationship between changes in *NPL* and changes in capital. This means banks' *NPL* holdings increase when capital increases and vice versa. This finding is consistent with Shrieves and Dahl (1992), suggesting the unintended effects of higher capital requirements on credit risk. However, when risk is measured by risk-weighted assets, the relationships become negative, contrary to the findings by Shrieves and Dahl (1992) but consistent with Jacques and Nigro (1997). This together suggests that when capital ratio increases, banks reduce ex-ante investments in risk-weighted assets but, but at the same time, can have ex-post higher non-performing loans. The different signs on *NPL* and *RWA* raise

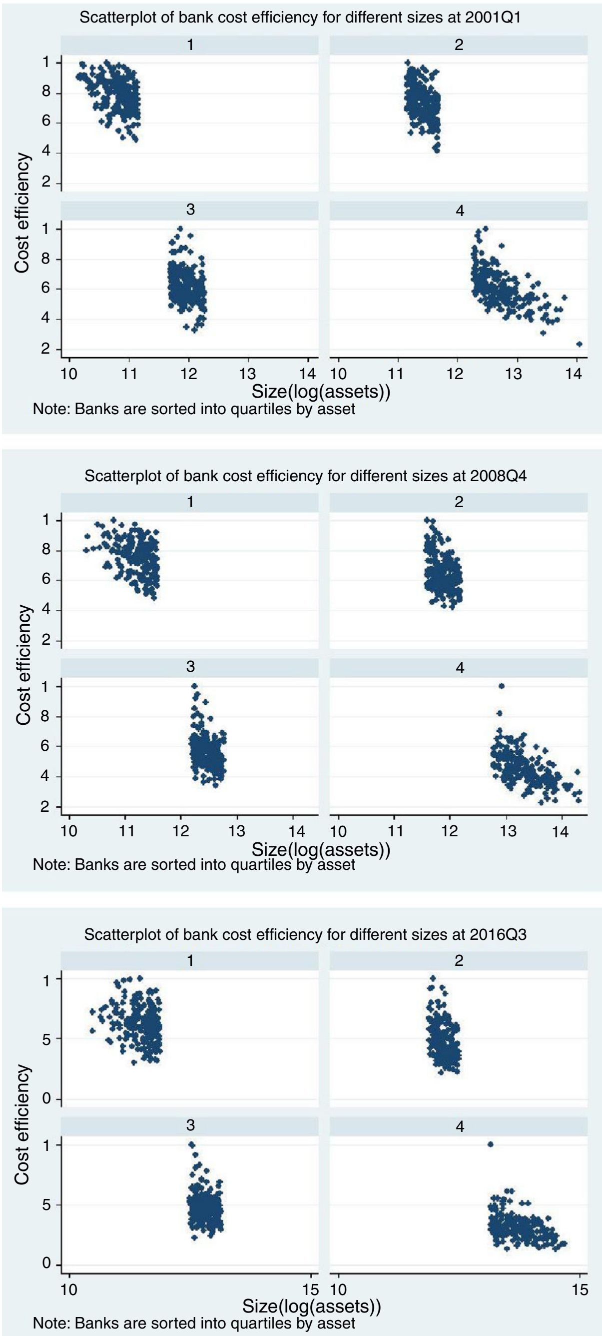

Figure 2 Scatterplots of cost efficiency for banks across different size groups at 3 periods.

concern whether risk-weighted assets are a credible measure of risk. It might be the case that banks ''optimize'' their capital by under-reporting *RWA* in an attempt to minimize regulatory burdens. Banks have two ways to boost their capital adequacy ratios: (i) by increasing the amount of regulatory capital held or (ii) by decreasing risk-weighted assets. Therefore, if banks capital adequacy ratios fall, banks' can immediately reduce risk-weighted assets to increase the capital ratio to meet the regulatory requirement. However, non-performing loans will still stay on the balance sheets and increase over time due to compounded unpaid interests. The high non-performing loans can erode bank's financial health despite having lower rates of risk-weighted assets.

With regard to efficiency, the results show a positive relationship between efficiency and change in *NPL* as well as change in capital, suggesting more efficient banks increase capital holdings and take on greater credit risk (*NPL*), supporting the ''skimping hypothesis''. This finding is contrary to the results by Kwan and Eisenbeis (1996) but consistent with Altunbas et al. (2007). While when risk is measured by *RWA*, efficiency and change in *RWA* are negatively related, implying that less efficient banks take on greater overall risk, supporting the moral hazard hypothesis.

Further, the results show the parameter estimates of lagged capital and risk are negative and highly significant. The coefficients show the expected negative sign and lie in the required interval [0,-1]. The can be interpreted as the speed of capital and risk adjustment towards banks' target level (Stolz et al., 2004). The speed of risk adjustment is significantly slower than the capital adjustment, which is in line with findings by Stolz et al. (2004).

Regarding buffers, capital buffers are negatively related to adjustment in *RWA*. This finding is consistent with Vallascas and Hagendorff (2013) and according to them it might be a sign that banks under-report their portfolio risk.

Impact of regulatory pressures on changes in capital and risk

One important goal of this study is to assess what impact the risk-based capital standards had on changes in bank capital ratios, portfolio risk, and efficiency levels. To answer this question, an examination of the dummy *REG* and its interaction term provides some interesting insights. The negative coefficients of *REG* on both capital equations suggest that banks with low capital buffers increase capital by less than banks with large capital buffers. This result reflects the desire of very-well capitalized banks to maintain a large buffer stock of capital, and the regulatory capital requirement was effective in raising capital ratios among banks which were already in compliance with the minimum risk-based standards. The parameter estimates of *REG* are negative and significant on ΔNPL but positive and significant on ΔRWA, suggesting that banks with low capital buffers reduce their level of nonperforming loans by more but decrease overall risk-weighted assets by less than banks with high capital buffer. The dummy *REG* has a positive sign on both efficiency equations, implying banks with lower capital buffer has higher cost efficiency than banks with high capital buffer.

The interaction terms $REG \times Risk_{t-1}$ and $REG \times Cap_{t-1}$ shed further light on how the speed of adjustment towards the target level depends on the size of the capital buffer. The coefficients on $REG \times Cap_{t-1}$ are significant and positive, indicating that banks with low capital buffer adjust capital toward their targets faster than better capitalized banks. This is in line with the study by Berger et al. (2008) in which they find that poorly capitalized and merely adequately capitalized banks adjust toward their capital targets at a faster speed than do already well capitalized banks. With respect to risk, we find that the coefficient of $REG \times Risk_{t-1}$ has the negative sign when risk is measured by *RWA* but becomes positive when risk is measured by *NPL*. The results suggest

Table 6.5 Two-step GMM estimations (FE) for the relationships between bank capital, cost efficiency and risk-taking

	Model where risk= NPL			Model where risk= RWA		
Variables	Y = ΔNPL	Y = ΔTier1 ratio	Y = Efficiency	Y = ΔRWA	Y= ΔTier1 ratio	Y= Efficiency
ΔCapital	0.0243*		0.0517*	−0.987*		0.0378*
	(0.00313)		(0.00612)	(0.00615)		(0.00694)
ΔRisk		0.00686*	−0.00509		−0.00866*	−0.00967*
		(0.00246)	(0.00456)		(0.000192)	(0.00236)
Efficiency	0.00439*	0.00117*		−0.114*	0.000474*	
	(0.00103)	(0.000214)	(0.00192)	(0.000174)		
$RISK_{t-1}$	−0.263*			−0.320*		
	(0.00139)			(0.00122)		
Cap_{t-1}		−0.947*			−0.934*	
		(0.00129)			(0.000497)	
Buffer	0.00139	0.937*	−0.266*	−0.223*	0.925*	−0.265*
	(0.00126)	(0.00136)	(0.00243)	(0.00263)	(0.000494)	(0.00244)
Size	0.124*	−0.00482	−8.505*	−1.099*	−0.0156*	−8.507*
	(0.0124)	(0.00318)	(0.0175)	(0.0232)	(0.00210)	(0.0175)
ROA	−0.175*	0.0184*	0.761*	0.0972*	0.0175*	0.760*
	(0.00545)	(0.00111)	(0.0106)	(0.0100)	(0.000910)	(0.0106)
LLP ratio	0.323*	−0.0451*	0.275*	−0.400*	−0.0477*	0.270*
	(0.00583)	(0.00122)	(0.0111)	(0.0105)	(0.000955)	(0.0112)
LTD	−0.000540***	−0.00145*	0.0150*	0.163*	−0.000988*	0.0155*
	(0.000305)	(5.88e−05)	(0.000605)	(0.000683)	(5.29e−05)	(0.000620)
REG	−0.111*	−0.298*	0.773*	2.000*	−0.234*	0.773*
	(0.0143)	(0.0413)	(0.0217)	(0.214)	(0.0229)	(0.0217)
Crisis	0.0300*	0.0313*	1.474*	0.293*	0.0322*	1.473*
	(0.00886)	(0.00144)	(0.0173)	(0.0166)	(0.00150)	(0.0173)
REG*$RISK_{t-1}$	0.0344*			−0.0223*		
	(0.00387)			(0.00268)		
REG*Δ CAP	0.00301			−0.151*		
	(0.0154)			(0.0290)		
REG*Cap_{t-1}		0.0357*			0.0286*	
		(0.00418)			(0.00232)	
REG*Δ Risk		−0.0122*			0.00731*	
		(0.00273)			(0.000520)	
GDP growth	−11.81*	−0.316*	11.99*	25.04*	0.0444	12.32*
	(0.476)	(0.0838)	(0.946)	(0.888)	(0.0808)	(0.947)
Spcs growth	−2.418*	−0.108*	23.31*	3.186*	−0.0779*	23.34*
	(0.142)	(0.0229)	(0.277)	(0.264)	(0.0240)	(0.277)
Hansen *J* statistic	0.063	0.097	0.217	1.403	0.92	0.233
	(0.8019)	(0.7553)	(0.6414)	(0.1084)	(0.3374)	(0.6295)
No. of observations	265,905	265,905	265,985	265,905	265,905	265,985
Number of banks	7644	7644	7725	7644	7644	7725

Notes: Standard errors in parentheses.
* $p<0.1$.
**$p<0.05$.
*** $p<0.01$.

that banks with low capital buffer adjust *NPL* faster but adjust *RWA* slower than banks with high capital buffers.

The interaction terms of $REG_{i,t} \times \Delta Cap_{i,t}$ and $REG_{i,t} \times \Delta Risk_{i,t}$ represent the impact of capital buffer on the management of short term risk and capital adjustments. We find that the coefficient on $REG_{i,t} \times \Delta Cap_{i,t}$ is insignificant when risk is measured by *NPL* but is significant and negative when risk is measured *RWA*. This finding indicates that banks with low capital buffer reduce overall risk-taking when capital is increased. We also find the coefficient on $REG_{i,t} \times \Delta Risk_{i,t}$ is significant and negative when risk is measured by *NPL* but is significant and positive when risk is measured *RWA*, suggesting that banks with low capital buffer reduce capital holding when *NPL* is increased but increase capital holding when *RWA* is increased.

Variables affecting optimal capital structure and efficiency levels

With regards to the bank specific variables, we find that larger banks (in terms of total assets) tend to be less cost efficient, implying dis-economies of scale for banks. This results are contrary to previous studies where they find large institutions tend to exhibit greater efficiency associated with higher scale economies (Wheelock and Wilson, 2012; Hughes and Mester, 2013). Bank size (*SIZE*) has a significant and negative effect on changes in capital and *RWA* but positive effect on changes in *NPL*. The finding is consistent with literature that larger banks generally have lower degrees of capitalization (Shrieves and Dahl, 1992; Aggarwal and Jacques, 2001; Rime, 2001; Stolz et al., 2004 and etc.). Larger banks have larger investment opportunity sets and are granted easier access to capital markets (Ahmad et al., 2008), which renders their target capital level smaller than the target capital levels of smaller banks. The negative relationship between size and change in *RWA* can be explained as larger banks are believed to be more diversified and could contribute to a reduction of their overall risk exposure (Lindquist, 2004). The results also show that size has a positive impact on change in *NPL*, suggesting larger banks tend to increase credit risk (*NPL*) more than smaller banks. This can be attributed to their *Too-Big-To-Fail* position, whereby larger banks believe any distress will be bailed out by government assistance.

In addition, the results support the findings of Stolz et al. (2004) and Altunbas et al. (2007) that profitability (measured by ROA) and capital are strongly positively related. Hence, banks seem to rely strongly on retained earnings in order to increase capital. The coefficient of loan loss provision ratio on ΔNPL ratio is positive but negative on ΔRWA ratio. The results are contrary to the finding of Aggarwal and Jacques (2001) where they find U.S. banks with higher loan loss provision have higher risk-weighted assets. Liquidity (measured by loan-deposit ratio) appears to be negatively related to change in capital and positively related to efficiency. There is a strong significant positive relationship between liquidity and change in *RWA*. Banks with more liquid assets need less insurance against a possible breach of the minimum capital requirements. Therefore banks with higher liquidity generally have smaller target capital levels and may also be willing to take on more risk.

Subsample estimation

Banking type characteristics may lead to different business strategies regarding bank lending and capital or cost management, which can result in differences in profitability and risk (Camara et al., 2013). Thus we consider three types of banks: commercial, cooperative and savings banks. Profit maximization is the traditional objective of commercial banks. However, mutual & cooperative banks are owned by their customers and might thus put their interests first (Altunbas et al., 2001). Their core business is often lending and taking deposits from individuals and small business. Savings banks, on the other hand, are generally held by stakeholders such as local or regional authorities and mainly depend on deposit. Moreover, mutual & cooperative and savings banks might experience difficulties in raising capital as much as they would like. We test the robustness of the results by running specifications on each type of banks separately.

Size is also a key factor determining the way credit and market risk, and capitalization levels affect efficiency. Therefore we investigate whether capital strategies differ for large and small banks. We also report estimates derived by using samples of the most and least cost efficient banks defined as the top quartile or bottom quartile cost efficient banks. The aim here is to see if the relationships differ if we look only at relatively cost efficient or inefficient banks.

Overall, estimates on sub-samples are largely consistent with full sample estimates. Table A.1 reports the results for equation where $\Delta Risk$ is used as the dependent variable. The results suggest that cooperative banks decrease risk (*RWA*) more than commercial banks and savings banks do when capital increases. With respect to the impact of capital buffer on the management of short term risk and capital adjustments, we find that the coefficient on $REG_{i,t} \times \Delta Cap_{i,t}$ is significantly negative for commercial banks, insignificant for cooperative banks and significantly positive for commercial banks when risk is measured by *RWA*. This finding indicates that commercial banks with low capital buffer reduce overall risk taking when capital is increased while savings banks with low capital buffer increase overall risk taking when capital is increased. The table also shows that for large banks with low capital buffers, capital and risk adjustments are positively related while for small banks with low capital buffers, the relationship is negative.

The capital equation in Table A.2 shows that bank size has a significant and negative effect on changes in capital for the most efficient banks but positive effect for the least efficient banks. The efficiency equation indicates that increase in capital increase cost efficiency of commercial banks while adjustments in capital do not appear to have any significant impact on efficiency levels for cooperative and savings banks.

Conclusion

Firm' ability to effectively allocate capital and manage risks is the essence of their production and performance. This paper has provided an understanding on the frontier methodology as a tool for performance measurement. Specifically, we assess the relationships between firm efficiency, capital allocation and risk, using data on a large sample of U.S. banks over the period of 2001–2016. We further look at their relationship by dividing the sample into different size and ownership classes, as well as the most and least efficient banks. Efficiency analysis is conducted using distance functions to model the technology and obtain X-efficiency measures as the distance from the efficient frontier.

The empirical evidence suggests that more efficient banks increase capital holdings and take on greater credit risk (*NPL*) while reduce overall risk (*RWA*). This study also finds evidence that capital buffer has an impact on capital and risk adjustments as well as cost efficiency. Moreover, it appears that increasing the capital buffer impacts risk-taking by banks depending on their level of cost efficiency, which is a placeholder for how productive their intermediation services are performed. More cost efficient banks that are well-capitalized tend to maintain relatively large capital buffers versus banks that are not. An additional finding, which is quite important, is that the direction of the relationship between risk-taking and capital buffers differs depending on what measure of risk is used.

This study accounts for the endogeneity of risk and capital decisions in firm production and would provide useful insights to managers on firm performance and important implications for banks as well as other organizations. It will be useful to consider in future research the relevance of the proposed methodology in other industries or across countries. This will also help to assess how different industries and institutional characteristics may impact on firm capital structure and risk decisions and how in turn these choices may affect firm performance.

Appendix

Table A.1 Estimation for different subsamples: risk equation.

	Commercial banks	Cooperative banks	Savings banks	Large banks	Small banks	Most efficient	Least efficient
	Model where risk= RWA Equation 1: DEP = △RWA						
△Capital	−0.962***	−2.161***	−1.113***	−0.800***	−0.984***	−0.973***	−0.994***
Efficiency	−0.119***	−0.0998***	−0.102***	−0.295***	−0.114***	−0.233***	−0.129***
$RISK_{t-1}$	−0.337***	−0.130***	−0.164***	−0.337***	−0.325***	−0.397***	−0.328***
Buffer	−0.232***	−0.147***	−0.117***	−0.362***	−0.226***	−0.260***	−0.271***
Size	−1.122***	−0.602**	−0.927***	−2.947***	−1.161***	−1.635***	−1.420***
ROA	0.0742***	1.373***	0.494***	0.0427	0.0995***	0.000887	0.105***
LLP ratio	−0.408***	0.0533	−0.230***	−0.377***	−0.397***	−0.396***	−0.347***
LTD	0.177***	0.0203***	0.0498***	0.152***	0.166***	0.201***	0.167***
REG	1.883***	7.824**	3.786***	−0.460	2.211***	3.626***	0.519
Crisis	0.305***	0.209*	0.235***	0.0228	0.302***	0.224***	0.310***
REG*$RISK_{t-1}$	−0.0209***	−0.111**	−0.0460***	0.00941	−0.0249***	−0.0413***	−0.00387
REG*△ CAP	−0.172***	−0.110	0.355**	0.442***	−0.183***	−0.0995	−0.147***
GDP growth	24.96***	14.70**	19.00***	23.20***	24.86***	24.39***	23.15***
Home index growth	2.951***	3.182*	4.194***	4.401***	2.993***	2.503***	3.353***
Observations	249,647	2804	13,348	9245	256,619	61,604	72,114
Number of banks	7209	68	372	565	7495	2448	2781
	Model where risk= NPL Equation 1: DEP = △NPL						
△Capital	0.0235***	0.0138	0.0348***	0.0639***	0.0237***	0.0269***	0.0167***
Efficiency	0.00552***	−0.0234**	−0.00615*	0.0181***	0.00304***	0.0273***	0.00832***
$RISK_{t-1}$	−0.264***	−0.306***	−0.239***	−0.143***	−0.268***	−0.391***	−0.222***
Buffer	0.00232*	−0.00345	−0.00487	−0.0174***	0.000901	−0.00359	−0.000199
Size	0.135***	−0.0327	−0.0142	0.273***	0.108***	0.138***	0.196***
ROA	−0.180***	−0.0498	−0.0137	−0.112***	−0.177***	−0.238***	−0.120***
LLP ratio	0.318***	0.883***	0.512***	0.154***	0.327***	0.232***	0.332***
LTD	−0.000380	−0.00565***	−0.00249***	0.00124	−0.000605*	−0.00242***	−2.69e−05
REG	−0.114***	−0.191	−0.0798	−0.0817**	−0.106***	−0.180***	−0.0608**
Crisis	0.0343***	0.0947	−0.0342	−0.00641	0.0318***	0.0531***	0.0174
REG*$RISK_{t-1}$	0.0353***	0.141***	0.00200	0.00681	0.0325***	0.0868***	0.00637
REG*△ CAP	0.00436	0.402*	−0.0973	−0.120***	0.00767	0.0535	−0.0566**
GDP growth	−12.00***	−11.81***	−8.948***	−14.46***	−11.66***	−11.92***	−11.15***
Home index growth	−2.321***	−3.555***	−4.081***	−2.377***	−2.379***	−1.912***	−2.548***
Observations	249,646	2804	13,348	9245	256,618	61,604	72,114
Number of banks	7209	68	372	565	7495	2448	2781

Notes:
1. Large banks are banks with assets greater than 1 billion and small banks are banks with assets less than 1 billion.
2. Most efficient banks are banks in the top quartile of cost efficiency. Least efficient banks are banks in the bottom quartile of cost efficiency.

* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

Table A.2 Estimation for different subsamples: capital equation.

	Commercial banks	Cooperative banks	Savings banks	Large banks	Small banks	Most efficient	Least efficient
	Model where risk= RWA Equation 2: DEP = △CAP(Tier 1 ratio)						
△Risk(RWA)	−0.00705***	−0.0567***	−0.0268***	−0.00727***	−0.00769***	−0.00477***	−0.00767***
Efficiency	0.000432**	0.0151***	0.00423***	−0.00103	0.000693***	−0.00366***	0.000991***
Cap_{t-1}	−0.941***	−0.732***	−0.847***	−0.916***	−0.937***	−0.961***	−0.934***
Buffer	0.932***	0.713***	0.832***	0.905***	0.928***	0.950***	0.924***
Size	−0.0195***	0.0285	0.131***	0.0289	−0.0180***	−0.0201***	0.00728*
ROA	0.0181***	0.0316	0.0524***	0.0155***	0.0173***	0.0104***	0.0211***
LLP ratio	−0.0453***	−0.161***	−0.0972***	−0.0447***	−0.0468***	−0.0376***	−0.0511***
LTD	−0.00109***	−0.000950	−0.000425	0.000505	−0.00108***	−0.00122***	−0.000504***
REG	−0.332***	1.271**	0.00729	−0.166*	−0.301***	−0.316***	−0.425***
Crisis	0.0326***	0.0493**	0.0179*	0.0234***	0.0330***	0.0246***	0.0366***
REG*Cap_{t-1}	0.0394***	−0.129**	−0.00164	0.0212**	0.0357***	0.0361***	0.0477***
REG*△ Risk	−0.00592***	−0.00486	0.00437	−0.0104*	−0.00521***	−0.00128	−0.00981***
GDP growth	0.0757	2.234**	−0.487	0.112	0.0336	−0.0450	0.286**
Home index growth	−0.0548**	−0.480	−0.558***	0.169	−0.112***	−0.183***	0.0620
Observations	249,646	2804	13,348	9245	256,618	61,604	72,114
Number of banks	7209	68	372	565	7495	2448	2781
	Model where risk= NPL Equation 2: DEP = △CAP(Tier 1 ratio)						
△Risk(NPL)	0.0390***	0.0501***	−0.00800	0.110***	0.0372***	0.0261***	0.0453***
Efficiency	0.000498***	0.0212***	0.00531***	−0.00167	0.000790***	−0.00354***	0.00110***
Cap_{t-1}	−0.949***	−0.839***	−0.878***	−0.917***	−0.946***	−0.967***	−0.944***
Buffer	0.940***	0.816***	0.860***	0.909***	0.937***	0.955***	0.933***
Size	−0.0182***	0.0731	0.148***	0.0249	−0.0159***	−0.0182***	0.00949**
ROA	0.0189***	−0.0583**	0.0442***	0.0142***	0.0179***	0.0138***	0.0195***
LLP ratio	−0.0431***	−0.196***	−0.0929***	−0.0376***	−0.0445***	−0.0328***	−0.0511***
LTD	−0.00173***	−0.00161**	−0.000975***	−0.000475	−0.00172***	−0.00164***	−0.00124***
REG	−0.305***	1.630**	−0.0566	−0.130	−0.271***	−0.296***	−0.405***
Crisis	0.0294***	0.0391*	0.0156	0.0174**	0.0300***	0.0234***	0.0321***
REG*Cap_{t-1}	0.0369***	−0.162**	0.00428	0.0191**	0.0329***	0.0342***	0.0461***
REG*△ Risk	−0.0444***	−0.0644	0.0175	−0.118***	−0.0419***	−0.0269***	−0.0546***
GDP growth	0.279***	1.947*	−1.134**	1.058**	0.194**	0.137	0.449***
Home index growth	−0.0869***	−0.746**	−0.708***	0.183	−0.146***	−0.220***	0.0445
Observations	249,644	2804	13,348	9245	256,616	61,604	72,114
Number of banks	7209	68	372	565	7495	2448	2781

Notes:
1. Large banks are banks with assets greater than 1 billion and small banks are banks with assets less than 1 billion.
2. Most efficient banks are banks in the top quartile of cost efficiency. Least efficient banks are banks in the bottom quartile of cost efficiency.

* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

Table A.3 Estimation for different subsamples: cost efficiency equation.

	Commercial banks	Cooperative banks	Savings banks	Large banks	Small banks	Most efficient	Least efficient
	Model where risk= RWA Equation 3: DEP = Efficiency						
ΔRisk(RWA)	-0.0105^{***}	-0.0464^{*}	-0.0140	-0.0177^{*}	-0.0108^{***}	-0.00672^{***}	-0.0122^{**}
ΔCapital	0.0396^{***}	-0.0984	0.00266	0.0719^{**}	0.0361^{***}	-0.00161	0.0561^{***}
Buffer	-0.273^{***}	-0.125^{***}	-0.185^{***}	-0.489^{***}	-0.267^{***}	-0.0875^{***}	-0.360^{***}
Size	-8.339^{***}	-11.83^{***}	-12.67^{***}	-12.02^{***}	-8.829^{***}	-4.774^{***}	-9.159^{***}
ROA	0.728^{***}	1.306^{***}	1.262^{***}	0.278^{***}	0.766^{***}	0.284^{***}	0.624^{***}
LLP ratio	0.268^{***}	-0.0933	-0.0849	0.186^{***}	0.263^{***}	0.0929^{***}	0.299^{***}
LTD	0.0225^{***}	0.00387	-0.0477^{***}	-0.00412	0.0157^{***}	0.00164^{***}	0.0245^{***}
REG	0.749^{***}	0.364	1.321^{***}	0.370^{***}	0.776^{***}	0.302^{***}	0.772^{***}
Crisis	1.392^{***}	1.299^{***}	2.397^{***}	0.841^{***}	1.430^{***}	0.399^{***}	1.672^{***}
GDP growth	11.62^{***}	12.49^{*}	17.48^{***}	6.407^{*}	11.87^{***}	1.024	16.75^{***}
Home index growth	23.08^{***}	16.59^{***}	22.31^{***}	4.504^{***}	22.69^{***}	12.00^{***}	11.71^{***}
Observations	249,647	2804	13,348	9245	256,619	61,604	72,114
Number of banks	7209	68	372	565	7495	2448	2781
	Model where risk= NPL Equation 3: DEP = Efficiency						
ΔRisk(NPL)	0.157^{***}	1.124^{***}	1.440^{***}	-0.111	0.237^{***}	0.00737	0.0885^{***}
ΔCapital	0.0496^{***}	-0.00577	-0.0243	0.0974^{***}	0.0441^{***}	0.00839	0.0731^{***}
Buffer	-0.273^{***}	-0.130^{***}	-0.180^{***}	-0.495^{***}	-0.266^{***}	-0.0882^{***}	-0.361^{***}
Size	-8.344^{***}	-11.73^{***}	-12.58^{***}	-12.02^{***}	-8.835^{***}	-4.773^{***}	-9.161^{***}
ROA	0.730^{***}	1.059^{***}	0.990^{***}	0.277^{***}	0.767^{***}	0.287^{***}	0.621^{***}
LLP ratio	0.268^{***}	-0.470^{*}	-0.277^{***}	0.195^{***}	0.260^{***}	0.0976^{***}	0.298^{***}
LTD	0.0211^{***}	0.00111	-0.0511^{***}	-0.00478	0.0141^{***}	0.00110^{*}	0.0232^{***}
REG	0.746^{***}	0.249	1.324^{***}	0.371^{***}	0.770^{***}	0.301^{***}	0.771^{***}
Crisis	1.375^{***}	1.110^{***}	2.268^{***}	0.854^{***}	1.404^{***}	0.399^{***}	1.661^{***}
GDP growth	13.23^{***}	21.94^{***}	28.85^{***}	4.327	14.36^{***}	0.917	17.32^{***}
Home index growth	23.01^{***}	16.04^{***}	24.47^{***}	4.393^{***}	22.62^{***}	11.97^{***}	11.70^{***}
Observations	249,646	2804	13,348	9245	256,618	61,604	72,114
Number of banks	7209	68	372	565	7495	2448	2781

Notes:
1. Large banks are banks with assets greater than 1 billion and small banks are banks with assets less than 1 billion.
2. Most efficient banks are banks in the top quartile of cost efficiency. Least efficient banks are banks in the bottom quartile of cost efficiency.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

References

Aggarwal, R., Jacques, K.T., 2001. The impact of fdicia and prompt corrective action on bank capital and risk: Estimates using a simultaneous equations model. J. Bank. Finance 25, 1139–1160.

Ahmad, R., Ariff, M., Skully, M.J., 2008. The determinants of bank capital ratios in a developing economy. Asia-Pac. Financ. Mark. 15, 255–272.

Aigner, D., Lovell, C.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econ. 6, 21–37.

Altunbas, Y., Evans, L., Molyneux, P., 2001. Bank ownership and efficiency. J. Money Credit Bank., 926–954.

Altunbas, Y., Carbo Valverde, S., Molyneux, P., 2003. Ownership and performance in European and us banking – a comparison of commercial, co-operative and savings banks. In: Fondacion de las Cajas de Ahorros Working Paper.

Altunbas, Y., Carbo, S., Gardener, E.P., Molyneux, P., 2007. Examining the relationships between capital, risk and efficiency in european banking. Eur. Financ. Manage. 13, 49–70.

Battese, G., Coelli, T., 1992. Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. J. Prod. Anal. 3, 153–169.

Berger, A.N., DeYoung, R., 1997. Problem loans and cost efficiency in commercial banks. J. Bank. Finance 21, 849–870.

Berger, A.N., Hunter, W.C., Timme, S.G., 1993. The efficiency of financial institutions: a review and preview of research past, present and future. J. Bank. Finance 17, 221–249.

Berger, A.N., DeYoung, R., Flannery, M.J., Lee, D., Oztekin, O., 2008. How do large banking organizations manage their capital ratios? J. Financ. Serv. Res. 34, 123–149.

Camara, B., Lepetit, L., Tarazi, A., 2013. Ex ante capital position, changes in the different components of regulatory capital and bank risk. Appl. Econ. 45, 4831–4856.

Charnes, A., Cooper, W.W., Rhodes, E., 1979. Measuring the efficiency of decision-making units. Eur. J. Oper. Res. 3, 339.

Cornwell, C., Schmidt, P., Sickles, R.C., 1990. Production frontiers with cross-sectional and time-series variation in efficiency levels. J. Econ. 46, 185–200.

De Young, R., 1997. Measuring bank cost efficiency: don't count on accounting. Financ. Pract. Educ. 7, 20–31.

Hughes, J.P., Mester, L.J., 2013. Who said large banks don't experience scale economies? Evidence from a risk-return-driven cost function. J. Financ. Intermed. 22, 559–585.

Hughes, J.P., Lang, W., Mester, L.J., Moon, C.-G., et al., 1995. Recovering technologies that account for generalized managerial preferences: an application to non-risk-neutral banks. Technical Report Wharton School Center for Financial Institutions. University of Pennsylvania.

Jacques, K., Nigro, P., 1997. Risk-based capital, portfolio risk, and bank capital: a simultaneous equations approach. J. Econ. Bus. 49, 533–547.

Kane, E.J., 1995. Three paradigms for the role of capitalization requirements in insured financial institutions. J. Bank. Finance 19, 431–459.

Kumbhakar, S.C., 1990. Production frontiers, panel data, and time-varying technical inefficiency. J. Econ. 46, 201–211.

Kwan, S.H., Eisenbeis, R.A., 1996. An analysis of inefficiencies in banking: a stochastic cost frontier approach. Econ. Rev.-Fed. Reserve Bank San Francisco, 16.

Kwan, S., Eisenbeis, R.A., 1997. Bank risk, capitalization, and operating efficiency. J. Financ. Serv. Res. 12, 117–131.

Lee, Y.H., Schmidt, P., 1993. A Production Frontier Model with Flexible Temporal Variation in Technical Efficiency. The Measurement of Productive Efficiency: Techniques and Applications., pp. 237–255.

Lindquist, K.-G., 2004. Banks' buffer capital: how important is risk. J. Int. Money Finance 23, 493–513.

Meeusen, W., Van den Broeck, J., 1977. Efficiency estimation from Cobb–Douglas production functions with composed error. Int. Econ. Rev., 435–444.

Rime, B., 2001. Capital requirements and bank behaviour: empirical evidence for Switzerland. J. Bank. Finance 25, 789–805.

Schmidt, P., Sickles, R.C., 1984. Production frontiers and panel data. J. Bus. Econ. Stat. 2, 367–374.

Sealey, C.W., Lindley, J.T., 1977. Inputs, outputs, and a theory of production and cost at depository financial institutions. J. Finance 32, 1251–1266.

Shrieves, R.E., Dahl, D., 1992. The relationship between risk and capital in commercial banks. J. Bank. Finance 16, 439–457.

Stolz, S., Heid, F., Porath, D., 2004. Does capital regulation matter for bank behavior? Evidence for German savings banks. Discussion paper.

Vallascas, F., Hagendorff, J., 2013. The risk sensitivity of capital requirements: evidence from an international sample of large banks. Rev. Finance 17, 1947–1988.

Wheelock, D.C., Wilson, P.W., 2012. Do large banks have lower costs? New estimates of returns to scale for us banks. J. Money Credit Bank. 44, 171–199.