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The Influence of Capital Requirement of Basel III Adoption on Banks' Operating Efficiency: Evidence from U.S. Banks

Abstract: The United States is recognized as the largest economic entity in the world and its financial system has developed steadily through the guidance of the Federal Reserve System for over one hundred years. However, in recent years, the global economic downturn, coupled with the global COVID-19 pandemic, has led to an unprecedented economic depression and rapid decline in the United States financial sector. Although the U.S. government has gradually instructed banks to raise the core quantity but a giant crisis under the economic depression is still present. This study thus takes U.S. commercial banks as the subject of research and employs the two-stage bootstrapped truncated regression to investigate the impacts of increases in required Core, Tier 1, and total capital adequacy ratios on their efficiency.

Keywords: Banking, Capital requirement, Operating efficiency, Two-stage DEA, Bootstrap.

JEL Classification: N12; G32.

1. Introduction

The banking industry is highly leveraged and is well known for its strict regulations. If an equity ratio is relatively low, then when a bank's asset quality deteriorates, in particular due to a rise in its non-performing loan ratio or a lack of market liquidity caused by COVID-19, it will face a huge risk of default. In the past, to ensure the stable operations of banks, the Bank for International Settlements (BIS) put forward the Basel Capital Accord in 1988, which stipulates that the capital adequacy ratio of commercial banks should not be less than 8%, and published transnational norms that mainly regulate credit risk. However, the prevalence of regulatory capital arbitrage and the increase in scale and complexity of large banks and the financial economic environment highlighted its shortcomings. The 1996 amendments incorporated market risk into the calculation of capital demand and emphasized the significance of three pillars: the development and trend of the capital adequacy ratio, supervision and inspection by regulators, and market discipline.

Banking regulators around the world then quickly agreed to the new rules for the largest global banks, known as Basel III, in an effort to avoid a repeat of the global financial crisis that erupted in 2008. The agreement forces banks to raise capital reserves to create a more stable financial system. Under the agreement, commercial banks still allocate at least 8% of their risk-weighted assets to cover potential losses, but in addition they must add a “capital protection buffer” of no less than 2.5% of their risky assets, and bank regulators shall impose an arbitrary counter-cyclical buffer of 2.5% during periods of high credit expansion, so as to protect the banking industry from losses during periods of excessive credit growth and financial stress. This significantly increased the minimum capital adequacy ratio of banks from 8% to 13%, while at the same time meeting the standard of no more than a 50% tier 2 capital ratio. In order to meet the capital adequacy requirements, especially the tier 1 capital ratio, commercial banks need to inject more common equity. As the cost to raise equity capital is much higher than other ways of financing, such as issuing bonds, etc., the increase in operating costs will affect the performance of bank management. Thus, an urgent problem that needs to be solved is how commercial banks can achieve steady development by increasing their input-output ratio and control operating costs to improve business performance (Roy et. al., 2021).

This study focuses on U.S. banks and explores how they can maintain their sound development by providing operational efficiency in the context of the enhanced requirements of Basel III on the core capital adequacy ratio and Tier 1 capital adequacy ratio. This paper analyses the input-output efficiency of banks through empirical analysis and data envelopment analysis and puts forward feasible suggestions to help them improve efficiency and maintain stability of the financial system.

Data envelopment analysis (DEA) was set up by Charnes, Cooper and Rhodes in 1978, which extended the concept of Farrell (1957). This method mainly takes maintaining decision-making units (DMUs) and output or input in a certain value and uses mathematical analysis tools on statistical related data. Its advantage is that it does not need to set up a function and can measure multiple inputs and multiple outputs. Therefore, this research method has been widely used in the analysis of efficiency output in the financial industry (Sherman and Gold, 1985; Seiford and Zhu, 1999; Banker, Chang and Lee, 2010; Curie, Guarda, Lozano Vivas and Zelenyuk, 2013; Curie and Lozano Vivas, 2015).

According to the literature review, many scholars adopt the two-stage analysis method. The first stage assumes that there is a role unit DMU, which uses multiple inputs and produces multiple outputs. Because one cannot observe the real set of production possibilities, we must use the observable input-output samples to estimate. The second stage takes the estimated value of DEA model in the first stage to analyse the impact of environmental variables on business efficiency via a regression model. According to Simar and Wilson (2007) and Li and Hu (2010), it is mainly the shadow price of limited samples of the DEA model that determines whether the efficiency is equal to 1, rather than the nature of potential variables. Therefore, the best analysis method in the second stage should be the truncated regression model. The analysis method used in this study is also a backtracking regression model that helps us to explore the impact of capital adequacy requirements on the operating efficiency of the U.S. banking industry.

2. Literature Review

The capital adequacy ratio reflects the extent to which a commercial bank can absorb losses with its own capital before depositors and creditors suffer losses on their assets. Research on the correlation between the capital adequacy ratio and bank operation efficiency mainly focuses on the following aspects. First, looking at the correlation between the business cycle and capital adequacy ratio, some scholars studied the optimal value management of a capital buffer. Second, from the perspective of risk management, traditional scholars noted that in order to maintain a certain level of capital, banks will reduce high-risk speculation (Shobande, & Shodipe, 2021). On the contrary, some scholars found that the capital adequacy ratio will increase the high-risk behaviour of banks. Some scholars have analysed the impact of capital requirements on bank risk management from the perspective of deposit insurance and considered the relationship between cost and income to carry out risk management (Vučinić, 2020). Finally, scholars from different countries put forward different views on how to improve the operational efficiency of banks under regulatory constraints.

Jokipii and Milne (2006), Aikman, Bridges, Kashyap and Siegert (2019), and Garcia (2019) stated that banks will maintain asset liquidity in a counter-cyclical manner and increase their capital buffer to make it consistent with business cycle fluctuations and to control credit risk, portfolio risk, and arbitrage risk. Chami and Cosimano (2010), Hyun and Rhee (2011), and Rime (2001) pointed out that banks may hold a higher proportion of capital in order to meet regulatory requirements. When the capital adequacy ratio is close to the prescribed level, a sufficient capital buffer can prevent regulatory intervention, but there is no risk management. Borio, Furline and Lowe (2001) offered that if banks reduce loans to maintain a high capital adequacy ratio, then this will decrease the capital supply of financial markets, and economic development will slow down.

Wheelock and Wilson (2000), Beltratti and Stulz (2012) presented that the higher the bank capital, the lower the probability of failure. Jokipii and Milne (2008) found that during an economic recession, loan loss reserves increase, which leads to a decrease in the capital ratio. Therefore, traditional scholars (Dewatripont and Tirole, 1994; Berger, Herring and Szegö, 1995; Keeley and Furlong, 1990) believe that banks will reduce risk speculations to maintain a certain capital level.

Some scholars have shown that an adjustment to the capital adequacy ratio will increase the risk behaviour of banks (Flannery, 1989; Gennotte and Pyle, 1991; Rochet, 1992; Besanko and Kanatas, 1996; Blum, 1999; Keeley and Furlong, 1990). Others stated that although capital requirements enhance the stability of banks, unregulated banks will take on too much portfolio and leverage risk to maximize shareholder value at the expense of deposit insurance.

Blum (1999) and Shim (2010) noted how capital regulatory requirements reduce the feasibility of increasing risky assets in a portfolio. Only by selecting the appropriate risk weighted asset portfolio to prevent and control risk can banks adhere to the role that the capital adequacy ratio plays and to ensure their stable operations. Gennotte and Pyle (1991) pointed out that capital requirements will increase the marginal cost of banks. However, the existence of deposit insurance may lead to moral hazard and increase the weight of risky assets to improve profitability. Milne (2002) believed that banks will balance the relationship between cost and income under capital requirements and strive to maximize profits under the condition of controllable costs.

According to the correlation analysis of capital and risk, Flannery (1989), Keeley and Furlong (1990) showed that bank capital is negatively correlated with risk. Calem and Rob (1999) further pointed out that the correlation curve between capital position and risk is U-shaped. The risk decreases with the increase of capital, but rises with the increase of capital when it exceeds the critical value. Rime (2001) took Swiss banks as an example and found a significant positive correlation between the capital adequacy ratio and bank risk-taking. Wheelock and Wilson (2000) showed that according to the indicators used by regulators to evaluate banks, banks with high leverage, low yield, low liquidity, or a risky asset portfolio are prone to bankruptcy.

There are two different views on the relationship between capital regulatory constraints and bank performance. Banker et al. (2010) used data of South Korean commercial banks from 1995 to 2005 to conduct an empirical analysis and found a positive correlation between the capital adequacy ratio and bank performance. Guidara, Lai, Soumaré and Tchana (2013) presented that Canada successfully avoided the financial crisis in 2008 due to sufficient capital. According to Posner (2015), the main function of higher capital levels is to reduce the motivation to take risks. Banks with higher capital to asset ratios are able to borrow at lower interest rates and obtain loans with economies of scale.

Bailey, Klein and Schardin (2017) and Tarullo (2019) believed that the Dodd-Frank Act in the U.S. proposes prudential regulation and higher capital requirements, so that financial institutions can better cope with financial stress events and crises. Darrell (2019) noted that market discipline will provide sufficient capital and liquidity for large banks and investment banks, while radical regulation is unnecessary or counterproductive.

Bernanke (2018), and Bitar and Peillex (2019), respectively conducted empirical analysis on the China' banking industry, the U.S. banking industry, and Islamic banks, finding that capital regulatory requirements are conducive to improving their operating performance. Greenwood, Hanson, Stein and Sunderam (2017) proposed three core design principles for strengthening and optimizing bank capital regulation: comprehensive constraint, post-processing regulatory arbitrage, and focusing on dynamic flexibility. Reducing the dependence on multiple rules such as the venture capital ratio and leverage ratio will help to solve the problem of regulatory arbitrage and give regulators more flexibility.

Researchers such as Barth, Caprio and Levine (2001, 2004) by contrast showed that capital constraints indirectly restrict the investment activities of banks and affect the profitability of banks. Kashyap and Stein (2004) pointed out that the capital requirements of Basel II may lead to an increase of the credit default rate during economic recession.

Behn, Haselmann Wachtel (2016) used the model-based regulatory institutional structure introduced in Germany and combined it with the impact of external entities to determine the procyclical impact of risk sensitive capital regulation on bank lending behaviour and corporate capital acquisition as a whole. Wilf (2016) found that investors believe that Basel III is credible, but there is a negative impact on companies subject to Basel III. Investors are less likely to sell or buy shares of regulated banks than expected, and shares of foreign regulated banks are also likely to fall.

How can banks create more performance under regulatory constraints? Chen, Sun and Peng (2005) pointed out that the group operation mode is conducive to performance improvement, and that banks' operation efficiency under a financial holding company group is higher than that of non-group banks in Taiwan. Chiu, Jan, Shen and Wang (2008) and Wang (2014) took the Bank of Taiwan as the research object, analysed its operation efficiency, and found that the capital adequacy ratio can be an important indicator to measure bank efficiency. Cheng, Liang and Chen (2015) explained that the increase in the proportion of common shares reduces the cost efficiency of financial holding companies, but has a positive impact on independent banks. Chen, Ho and Hsu (2014) pointed out that having an adequate capital buffer has a positive impact on the profitability of banks. Cheng et al. (2015) took the return on equity (ROE) of banks as compensation for the cost of capital caused by excess capital. Boyson, Fahlenbrach and Stulz (2016) stated that the optimal risk level of a bank depends on its franchise value. For banks with high franchise value, low risk and a high capital level are the best choice. When possible, constrained banks will use regulatory arbitrage to ease these restrictions.

3. Methodology

Suppose there are N DMUs. Each DMU employs k variable inputs $\underset{\sim}{x} = (x_1, \dots, x_k) \in \mathfrak{R}_+^k$ and r quasi-fixed inputs $\underset{\sim}{q} = (q_1, \dots, q_r) \in \mathfrak{R}_+^r$ to produce m outputs $\underset{\sim}{y} = (y_1, \dots, y_m) \in \mathfrak{R}_+^m$. The production possibility set of the CCR model, proposed by Charnes, Cooper and Rhodes (1978), is defined as:

$$\boldsymbol{\Omega} = \{(\underset{\sim}{x},\ \underset{\sim}{q},\ \underset{\sim}{y}) \mid \ \underset{\sim}{x} \ \geq \boldsymbol{X}\underset{\sim}{\lambda},\ \ \underset{\sim}{q} \ \geq \boldsymbol{Q}\underset{\sim}{\lambda},\ \ \underset{\sim}{y} \leq \boldsymbol{Y}\underset{\sim}{\lambda},\ \ \underset{\sim}{\lambda} \geq \underset{\sim}{0}\}, \tag{1}$$

where $\boldsymbol{X} = (\underset{\sim}{x}_1, \dots, \underset{\sim}{x}_N)$, $\boldsymbol{Q} = (\underset{\sim}{q}_1, \dots, \underset{\sim}{q}_N)$, $\boldsymbol{Y} = (\underset{\sim}{y}_1, \dots, \underset{\sim}{y}_N)$, $\underset{\sim}{\lambda}$ is an (N×1) vector of intensity variables, and $\underset{\sim}{0}$ is an (N×1) vector of zeros. Since the quasi-fixed inputs cannot be altered, the input-oriented technical efficiency (TE) is given by:

$$\hat{\delta}(\underset{\sim}{x},\ \underset{\sim}{q},\ \underset{\sim}{y}) = \underset{\delta,\ \underset{\sim}{\lambda}}{inf}\{\delta \mid \ (\delta\underset{\sim}{x},\ \underset{\sim}{q},\ \underset{\sim}{y}) \in \boldsymbol{\Omega}\}. \tag{2}$$

The CCR model assumes that production exhibits constant returns to scale (CRS), which is only appropriate when all DMUs are operating at an optimal scale. Banker, Charnes and Cooper (1984) extended the CCR model to account for variable returns to scale (VRS), calling it the BCC model. Mathematically, the BCC model is modified easily from the CCR model by adding the convexity constraint $\underset{\sim}{\mathbf{1}}'\underset{\sim}{\lambda} = 1$ in $\boldsymbol{\Omega}$, where $\underset{\sim}{\mathbf{1}}$ is an (N×1) vector of ones.

Many studies have computed the estimates $\hat{\phi}$ by the BCC model (or the CCR model) in the first stage and then regressed $\hat{\theta} = \frac{1}{\hat{\delta}}$ (or $\hat{\delta}$) on p environmental variables $\underset{\sim}{z} = (z_1, \dots, z_p) \in \Re^p$ in the second stage:

$$\hat{\theta}_n = \underset{\sim}{\beta}'\underset{\sim}{z}_n + \varepsilon_n \geq 1, \qquad n = 1,2 \dots, N, \tag{3}$$

where $\underset{\sim}{\beta}$ is a p×1 vector of parameters, and ε_n is a continuous iid random variable with mean zero and constant variance σ_ε^2. These studies viewed $\hat{\theta}_n$ as the realization of latent variables and estimated equation (3) by the tobit regression method.

Simar and Wilson (2007) indicated that there are several problems for this empirical model. First of all, the tobit specification is motivated by the observation that several efficiencies are equal to unity, suggesting a probability mass at one and a concept of latent variables. However, deciding whether efficiency will be one is primarily an artifact and not the property of latent variables. Hence, the second stage should utilize the truncated specification, and ε_n is distributed $N(0, \sigma_\varepsilon^2)$ with left truncation at $(1 - \underset{\sim}{\beta}'\underset{\sim}{z}_n)$ for each n.[1] Second, the dependent variable $\hat{\theta}_n$ cannot be observed directly and has to be estimated by the BCC model in the first stage. Hence, not only are $\hat{\theta}_n$ serially correlated, but the random distance ε_n in equation (3) is also correlated with environmental variables $\underset{\sim}{z}_n$. Third and finally, the DEA estimator obtained from the BCC model under mild assumptions

[1] Assume the regression model is, $y_n^* = \boldsymbol{\beta}'\underset{\sim}{\mathbf{x}}_n + \omega_n$, $n = 1, 2\dots, N$, where $\omega_n \sim N\left(0, \sigma^2\right)$. We cannot directly observe y_n^* and only obtain the information $y_n(\geqq 1)$. Let $\phi(.)$ and $\Phi(.)$ be the probability density function (pdf) and cumulative distribution function (CDF) of the standard normal distribution, respectively. The tobit regression model assumes $y_n = \begin{cases} y_n^* & \text{if } y_n^* > 1, \\ 1 & \text{if } y_n^* \leq 1. \end{cases}$ with a likelihood function:

$$L = \prod_{y_n > 1} \frac{1}{\sigma}\phi\left(\frac{y_n - \boldsymbol{\beta}'\underset{\sim}{\mathbf{x}}_n}{\sigma}\right) \prod_{y_n = 1} \Phi\left(\frac{1 - \boldsymbol{\beta}'\underset{\sim}{\mathbf{x}}_n}{\sigma}\right).$$

However, the truncated regression model is $y_n = y_n^*$ for all $y_n^* \geq 1$ with a likelihood function of:

$$L = \prod_{n=1}^{N} \frac{1}{\sigma}\phi\left(\frac{y_n - \boldsymbol{\beta}'\underset{\sim}{\mathbf{x}}_n}{\sigma}\right)\left[1 - \Phi\left(\frac{1 - \boldsymbol{\beta}'\underset{\sim}{\mathbf{x}}_n}{\sigma}\right)\right].$$

is consistent, but converges slowly at the rate $N^{\frac{-2}{(k+r+m+1)}}$, which is known as the curse of dimensionality (Kneip, Simar and Wilson, 2008). This suggests that even though the maximum likelihood (ML) estimators of $\underset{\sim}{\beta}$ in the second-stage regression are consistent, they are unlikely to obtain reliable conference intervals.[2] Since the structures of the above phenomena are not known to be associated with an extremely slowly convergent rate, Simar and Wilson (2007) proposed a bootstrap procedure to overcome these problems.

The efficiency score $\hat{\theta}_n$, by construction, is biased upward (Banker et al., 2010). Although it is consistent, the bias will disappear at a slow rate of $N^{\frac{-2}{(k+r+m+1)}}$. Simar and Wilson (2007) suggested another bootstrap procedure to correct this bias. The bias-corrected estimator of $\hat{\theta}_n$ is:

$$\hat{\hat{\theta}}_n = \hat{\theta}_n - \overline{BIAS}(\hat{\theta}_n), \tag{4}$$

where $BIAS(\hat{\theta}_n) \equiv E(\hat{\theta}_n) - \theta_n$, and $\overline{BIAS}(\hat{\theta}_n)$ is the bootstrap bias estimate.

Extending Simar and Wilson's double bootstrap procedure by taking into account quasi-fixed inputs, we describe the algorithm as follows.

[1] Use all DMUs to calculate $\hat{\theta}_n$ (n = 1, 2,…, N) by the BCC model.

[2] Acquire the ML estimates $(\hat{\underset{\sim}{\beta}}, \hat{\sigma}_\varepsilon)$ of $(\underset{\sim}{\beta}, \sigma_\varepsilon)$ in the truncated regression $\hat{\theta}_n = \underset{\sim}{\beta}' \underset{\sim}{z}_n + \varepsilon_n$, where ε_n are iid $N(0, \sigma_\varepsilon^2)$ with left truncation at $(1 - \underset{\sim}{\beta}' \underset{\sim}{z}_n)$ by all inefficient DMUs, where $\hat{\theta}_n > 1$, n = 1, 2,…, J (< N).

[3] For each DMU (n = 1,…, N), loop the following four steps ([3.1]~[3.4]) B_1 times to obtain a set of bootstrap estimates $\{\hat{\theta}^*_{nb}\}_{b=1}^{B_1}$:

[3.1] Draw ε_n^* randomly from $N(0, \hat{\sigma}_\varepsilon^2)$ with left truncation at $(1 - \hat{\underset{\sim}{\beta}}' \underset{\sim}{z}_n)$.

[3.2] Compute $\theta_n^* = \hat{\underset{\sim}{\beta}}'{}^{*}_{\sim n} n$.

[3.3] Set $\underset{\sim}{x}_n^* = \underset{\sim}{x}_n \frac{\theta_n^*}{\hat{\theta}_n}$, $\underset{\sim}{q}_n^* = \underset{\sim}{q}_n$, and $\underset{\sim}{y}_n^* = \underset{\sim}{y}_n$.

[3.4] Calculate $\hat{\theta}_n^*(\underset{\sim}{x}_n, \underset{\sim}{q}_n, \underset{\sim}{y}_n)$ by the BCC model with technology $(\boldsymbol{X}^*, \boldsymbol{Q}^*, \boldsymbol{Y}^*)$, where $\boldsymbol{X}^* = (\underset{\sim}{x}_1^*, \dots, \underset{\sim}{x}_N^*)$, $\boldsymbol{Q}^* = (\underset{\sim}{q}_1^*, \dots, \underset{\sim}{q}_N^*)$, and $\boldsymbol{Y}^* = (\underset{\sim}{y}_1^*, \dots, \underset{\sim}{y}_N^*)$.

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[2] The standard parametric estimators typically achieve a convergence rate of $N^{-1/2}$. For k = 2, r = 2, and m = 3, estimators obtained from the BCC have a convergence rate of $N^{-2/8}$. To achieve the same order of estimation errors that one attains with $N = 100$ under the convergence rate of $N^{-1/2}$, one needs $N = 10{,}000$ for the convergence rate of $N^{-2/8}$.

[4] For each DMU (n = 1,..., N), compute the bias-corrected estimate $\hat{\hat{\theta}}_n = \hat{\theta}_n - B\widehat{IA}S(\hat{\theta}_n)$, where $B\widehat{IA}S(\hat{\theta}_n) = \frac{1}{B_1}\sum_{b=1}^{B_1} \hat{\theta}^*_{nb} - \hat{\theta}_n$.

[5] Get the ML estimates $(\hat{\hat{\underset{\sim}{\beta}}}, \hat{\hat{\sigma}}_\varepsilon)$ of $(\underset{\sim}{\beta}, \sigma_\varepsilon)$ in the truncated regression of $\hat{\hat{\theta}}_n$ on $\underset{\sim}{z}_n$ with left truncation at $(1 - \underset{\sim}{\beta}' \underset{\sim}{z}_n)$.

[6] Loop the following three steps ([6.1]~[6.3]) B_2 times to obtain a set of bootstrap estimates $\left\{(\hat{\hat{\underset{\sim}{\beta}}}^*, \hat{\hat{\sigma}}^*_\varepsilon)_b\right\}_{b=1}^{B_2}$:

[6.1] For each DMU (n = 1,..., N), draw ε^{**}_n randomly from $N(0, \hat{\hat{\sigma}}^2_\varepsilon)$ with left truncation at $\left(1 - \hat{\hat{\underset{\sim}{\beta}}}'{}_{\sim n}()\right)$.

[6.2] For each DMU (n = 1,..., N), compute $\theta^{**}_n = \hat{\hat{\underset{\sim}{\beta}}}'{}^{**}_{\sim n n}$.

[6.3] Find the ML estimates $(\hat{\hat{\underset{\sim}{\beta}}}^*, \hat{\hat{\sigma}}^*_\varepsilon)$ of $(\underset{\sim}{\beta}, \sigma_\varepsilon)$ in the truncated regression of θ^{**}_n on $\underset{\sim}{z}_n$ with left truncation at $(1 - \underset{\sim}{\beta}' \underset{\sim}{z}_n)$.

[7] Use the original estimates $(\hat{\hat{\underset{\sim}{\beta}}}, \hat{\hat{\sigma}}_\varepsilon)$ and the bootstrap values obtained from step [6] to construct estimated confidence intervals for each element of $\underset{\sim}{\beta}$ and for σ_ε.

4. Empirical study

The United States is a special country with a distinct financial structure and it is also the largest economic entity recognized internationally. Through the Federal Reserve System, the United States has made its financial system develop steadily over the past century. It has been on the brink of many international financial crises and extricated itself from the difficulties successfully. This study thus focuses on commercial banks to examine whether different capital and capital adequacy ratios have a real effect on those in the United States from 2011 to 2019. We utilize data of U.S. commercial banks in the global banking database to explore and analyse the issues of global concern.

Based on most of the literature on bank efficiency, this paper uses the intermediary method to treat a bank as an intermediary of financial services and views it as an intermediary institution that chooses its number of employees, fixed assets, and total deposits as input variables. Many studies in the literature have considered net loans and portfolio investments as output variables (Huang and Kao, 2006; Valverde, Humphrey and Lopey del Paso, 2007; and Curie and Lozano-Vivas, 2015). Moreover, the major output of a bank is loans, but they are always a risky output because there is always an *ex-ante* risk for a loan to become non-performing. Non-performing loans (NPLs) are undesirable outputs to a bank and decrease its performance (Chang, 1999; Hu, Liu and Chiu, 2004; Gabriel, Wegayehu and Wissale, 2020). In order to satisfy the assumption of semi-positive output, we translate the value of NPLs by the maximum of NPLs such that the translated NPLs are equal to the maximum of NPLs minus the original NPLs. Therefore, the output variables in this study consist of performing loans (subtracting non-performing loans from all loans), translated NPLs, portfolio investments, and other revenues (Grubišić, Kamenković and Kaličanin, 2022). Table 1 reports the summary statistics of the inputs and outputs used in the analysis.

Table 1: Descriptive Statistics of Inputs and Outputs

Variable	Mean	Std. Dev.	Min	Max
Input				
Number of employees (persons)	4.7418	27.0668	0.0028	231.7992
Total deposits (NT$ million)	282.4558	15,83.2713	0.2088	13,389.8047
Fixed assets (NT$ million)	2.3678	11.9363	0.0046	102.6894
Output				
Performing loans (NT$ million)	182.4409	936.7607	0.1816	7,859.6136
Translated NPLs (NT$ million)	884.6694	47.7177	412.9375	892.0000
Portfolio investments (NT$ million)	1.1157	7.5137	0.0000	73.0359
Other revenue (NT$ million)	2.3491	14.6345	0.0003	143.6174

Notes: (1) Performing loans = Net loans minus NPLs. (2) Translated NPLs = US$892 million minus NPLs. (3) All nominal variables are deflated by the GDP deflator with 2010 as the base year.

Balk (2001) argued that actual technology should be treated as variable returns to scale (VRS) and that even though a DMU is technically efficient under VRS, it can additionally increase its productivity by improving its operating scale along the VRS frontier. As the output variable includes translated NPLs, this study employs the input-oriented BBC model, which is translation invariant with respect to outputs, to measure technical efficiency in the first stage.

Input and output variables in the DEA model should satisfy the property of isotonicity - that is, increased inputs cannot reduce outputs. Table 2 presents Pearson correlation coefficients of the input and output variables. All values are significantly positive at the 0.1% level, indicating that our selected input and output variables indeed meet the property of isotonicity.

Table 2: Pearson Correlation Coefficients between Input and Output Variables

	Performing Loans	Translated NPLs	Portfolio Investments	Other Revenue
Number of Employees	0.9751 (< 0.001)	0.9334 (< 0.001)	0.8514 (< 0.001)	0.9896 (< 0.001)
Total Deposits	0.9837 (< 0.001)	0.9276 (< 0.001)	0.8750 (< 0.001)	0.9845 (< 0.001)
Fixed Assets	0.9692 (< 0.001)	0.9058 (< 0.001)	0.8983 (< 0.001)	0.9840 (< 0.001)

Note: The values in parentheses are p-value, and all correlation coefficients are significant at the 0.1% level.

Empirical results show that the minimum efficiency is 0.7103 and the average efficiency is 0.9537. The second stage employs the bootstrapped truncated regression model, proposed by Simar and Wilson (2007), to investigate how the capital requirement affects the efficiency indicator $\hat{\theta}$ (reciprocal of input-oriented technical efficiency), which is the dependent variable in the bootstrapped truncated regression model. This study follows the regulation of Basel III to consider the capital requirement of three types: core Tier 1 capital (*Core*), Tier 1 capital (*Tier*1), and Tier 2 capital (*Tier*2); all three are defined as a percentage of risk-weighted assets (RWA).[3]

We also include control variables in the empirical model in order to truly reveal the impacts of capital requirements on banks' efficiency. Since the asset structure of a bank can be seen from the ratio of stakeholders' equity, the lower the ratio, the lower the net asset value of the bank. Once the deficit exceeds the net asset value, the interest of the depositors will be harmed. Hence, it can be used as a deciding factor to determine the ability of a bank to bear losses. Stiroh and Rumble (2006) and Mercieca, Schaeck and Wolfe (2007), suggested that economies of scale can effectively improve bank performance. Hence, the scale of banks is included in the empirical model.

$$\hat{\theta}_i = \beta_0 + \beta_1 Core_i + \beta_2 Tier1_i + \beta_3 Tier2_i + \beta_4 CS_i + \beta_5 Size_i + \varepsilon_i\,, \qquad (7)$$

where ε_i is distributed $N\left(0, \sigma_\varepsilon^2\right)$ with left-truncation at $\hat{\theta}_i \geq 1$ for each i. Table 3 presents the definitions and sample means of the variables used in the bootstrapped truncated regression model.

[3] Assume that the rise in capital quantity and quality is mandatory, instead of voluntary.

Table 3: Definitions and Sample Means of Variables Used in the Bootstrapped Truncated Regression Model

Variable	Definition	Mean	VIF
$\hat{\theta}$	Reciprocal of input-oriented VRS technical efficiency	1.3301	––
Core	100*Core Tier1 capital divided by risk-weighted assets (%)	0.1459	4.7498
*Tier*1	100*Tier 1 capital divided by risk-weighted assets (%)	12.9936	2.5686
*Tier*2	100*Tier 2 capital divided by risk-weighted assets (%)	1.2406	1.2531
CS	Capital structure (100*net value / total asset) (%)	10.6770	2.6228
Size	Natural logarithm of total assets (NT$ million)	2.7989	1.4737

Note: (1) All nominal variables are deflated by the GDP deflator with 2006 as the base year.

Multicollinearity, referring to the situation where there is either an exact or approximate exact linear relationship among explanatory variables, is an undesirable situation since it misleadingly inflates the standard errors. Thus, it makes some variables statistically insignificant when they otherwise should be significant. The variance inflation factor (VIF), based on the coefficient of determination (R^2) of auxiliary regressions, is generally used to detect multicollinearity. Chatterjee and Price (1991) suggested that values in excess of 10 are problematic. The last column of Table 3 shows that all values of VIF are less than 6. Hence, we can conclude that all explanatory variables used in our empirical model do not have the problem of multicollinearity. Table 4 presents the truncated regression results. Note that the covariate in the empirical model can improve technical efficiency (or reduce $\hat{\theta}$) if its coefficient is negative. The second column is the ML estimates of the truncated regression model where only the estimated coefficients of core Tier1 capital (*Core*), Tier1 capital (*Tier*1), and CS are significantly different from 0, among which *Core* is at the 10% level of significance while the others are at the 1% level of significance.

Table 4: Bootstrapped Truncated Regression Results

ML Estimate		Bootstrapped Truncated Regression Results						
	$\hat{\beta}$	Lower bound			$E(\hat{\beta}^*)$	Upper bound		
		0.5%	2.5%	5%		5%	0.5%	2.5%
Constant	1.8908***	1.4378	1.5150	1.5574	1.8891***	2.1920	2.2485	2.3710
Core	11.1626***	5.2130	7.0233	7.7790	11.2321***	14.5834	15.0203	16.1878
Tier1	-0.0428*	-0.0921	-0.0813	-0.0756	-0.0434**	-0.0107	-0.0043	0.0070
Tier2	-0.1439	-0.3279	-0.2928	-0.2738	-0.1438**	-0.0070	0.0269	0.0993
Size	-0.1227***	-0.1713	-0.1593	-0.1548	-0.1232***	-0.0880	-0.0823	-0.0614
CS	-0.1246***	-0.1787	-0.1688	-0.1605	-0.1247***	-0.0862	-0.0775	-0.0597
$\hat{\sigma}_{\varepsilon}$	0.1298***	0.2747	0.3032	0.3117	0.3568***	0.3961	0.4027	0.4118

Note: (1) *, **, and *** represent the 10%, 5%, and 1% levels of significance, respectively.
(2) $E(\hat{\beta}^*)$ is the average of the bootstrap set with 2,000 replications.

Simar and Wilson (2007) pointed out that the dependent variable $\hat{\theta}_i$ cannot be observed directly and must be estimated by the DEA model. Hence, not only are $\hat{\theta}_i$ serially correlated, but the random disturbance ε_i is also correlated with covariates. In addition, the DEA estimator obtained from the BCC model is consistent, but converges slowly at the rate $H^{-1/4}$, indicating that even though ML estimators of $\tilde{\beta}$ are consistent, they are unlikely to obtain reliable conference intervals. Taking advice from Simar and Wilson (2007), we use 2,000 replications in the bootstrapped procedure to construct estimates of confidence intervals. Columns 3-9 of Table 4 present the estimated results for the bootstrapped truncated regression model, among which Column 6 shows an average of 2,000 estimated values obtained through the bootstrapping method, Columns 3 and 9 are respectively the lower and upper boundaries of the 99% confidence interval, Columns 4 and 8 are respectively the lower and upper boundaries of the 95% confidence interval, and Columns 5 and 7 are respectively the lower and upper boundaries of the 90% confidence interval.

The estimated results of the bootstrapped truncated regression show the estimated coefficients of *Core*, *Tier1*, *CS*, and *Size* are significantly different from 0, among which *Size* is at the 5% level of significance, while the others are at the 1% level of significance. The estimated coefficient of *Size* is significantly larger than 0, while the corresponding ML estimate is insignificantly negative at the 10% level. We further discover that the estimated coefficients of the bootstrapped truncated regression are significantly negative at the 1% level, consisting of CS. Their corresponding ML estimates are smaller than the lower boundary of the 95% confidence interval of the bootstrapped results. Hence, the ML estimates tend to overestimate the impact of these variables on the technical efficiency of U.S. commercial banks.

After controlling the size and capital structure, we find that the estimated coefficient of core is significantly positive, which indicates that the growth of core will have a negative impact on bank performance; *Tier1* may have a negative significant result due to the deduction of core, while the level of *Tier2* is higher than Tier1 and has no significant difference with 0, indicating that the impact of *Tier2* can be ignored. Therefore, when banks tend to increase the BIS ratio to indicate their soundness, they tend to increase *Tier2* to reduce the negative impact on bank performance. This also shows that when a higher capital adequacy ratio is needed, banks are more willing to increase *Tier2* related to the cost of capital to meet the requirements, and the higher the capital structure, the higher the bank performance and the larger the bank scale, which will produce the effect of a scale economy. In this paper, we use Bank of America from 2011 to 2019 as a sample to test the impact of different types of capital on bank operating efficiency. The empirical results show, under the given control variables, the core capital will have a significant negative effect on bank efficiency, and *Tier2* capital will not impact bank efficiency, which is in line with the financing order of the banking industry. This shows that when output is constant, an increase of input will certainly reduce efficiency.

5. Discussion

In response to the deteriorating asset quality and liquidity from the dramatic market contraction due to insufficient capital adequacy ratios during the global financial crisis of 2007-2008, the Basel Committee proposed Basel III in September 2010. The objectives of Basel III are to raise the capital adequacy ratio gradually from 8% to 13% and the *Core* capital adequacy ratio from 2% to 4.5% by 2019. Therefore, the government authority of banks in Taiwan, the Financial Supervisory Committee, is requiring domestic banks to increase their capital to meet the new requirement of the capital adequacy ratio. Bank capital is composed of Core, Tier 1, and Tier 2. The portion of Tier 2 capital cannot exceed the portion of Tier 1 capital. In terms of the cost of capital, Core (*Core)* is the highest, and Tier 2 is the lowest. Tier 1 (*Tier1*), consisting of Core, also includes non-redeemable, non-cumulative preferred equity. Tier 2 (*Tier2*) is supplementary bank capital, including revaluation reserves, undisclosed reserves, hybrid instruments, and subordinated term debt. In terms of the capacity of risk absorption, Core is the best, and Tier 1 is better than Tier 2. Therefore, increasing Core and Tier 1 is costly to banks, but are more reliable than raising Tier 2. Put differently, banks will prefer raising cheaper Tier 2 to satisfy the new capital requirement.

The new capital requirement of Basel III, increasing Core and Tier 1 capital ratios, leads to better risk absorption, but less operating efficiency. However, if a bank supervisory authority believes that increasing the capital adequacy ratio and Core adequacy ratio can allow better integration into the global financial market and effectively lower the risk of bankruptcy, then banks should cooperate with the relaxing of regulation to allow those operating under better conditions to undertake more projects and increase outputs. Hence, to generate more profit, commercial banks would have more incentives to increase their capital adequacy ratio and fulfil the expectation of the bank supervisory authority.

This study employs data on domestic U.S. commercial banks between 2011 and 2019 as the sample to examine the impact of different types of capital on bank performance.[4] Empirical results show that, given control variables, Core and Tier 1 have a negative impact on bank performance, while Tier 2 does not affect bank performance. This corresponds with the financing order for bankers in terms of the cost of capital, and shows that when output is constant, efficiency drops as input increases.

We further conduct robustness analysis to investigate how robust our results are. After illustrating the Monte Carol simulation of bootstrapped truncated regression, Simar and Wilson (2007) offered an empirical example based on the paper by Aly, Grabowski, Pasurka and Rangan (1990), which incorporated revenue diversity into the empirical model to look at the efficiency of 432 U.S. commercial banks. We follow the measure used by Aly et. al. to construct revenue diversity as:

$$Div = -\ln \sum_{i=1}^{d} S_i^2 ,$$

where d is the total number of different revenue streams of the bank, and S_i equals the proportion of the i^{th} revenue to total revenue. The index *Div* takes a value of zero for single revenue banks and increases with more revenue diversity. We consider three types of bank revenue: provision of loan services (including business and individual loans), portfolio investment (mainly government securities and equity shares, along with public and private enterprise securities), and other revenues. In addition, Simar and Wilson not only took into account revenue diversity *Div*, but also included the interaction term *Size*×*Div* in the second-stage regression.

[4] The results reflect the situation after the 2008 global crisis.

Following the above studies, we input revenue diversity *Div* into the empirical model (7), called Model 2, and additionally include the interaction term *Size*×*Div*, called Model 3. The signs and magnitudes of estimated coefficients in Table 4 are similar to those in Table 5 except for *Size*, which is significantly different from zero at the 1% level in Table 4, but insignificant at the 10% level in Table 5. More importantly, in both Table 4 and Table 5 the coefficients of both *Core* and *Tier1* are significantly positive at the 5% level, and that of *Tier2* is insignificant at the 10% level. Furthermore, both *Div* and *Size*×*Div* are insignificantly different from zero at the 10% level in Table 5. Hence, we conclude that our empirical results in Table 4 are robust.

Table 5: Robustness Analysis of Bootstrapped Truncated Regression Results

	Model 2					Model 3				
	2.5%	5%	$E(\hat{\beta}^*)$	95%	97.5%	2.5%	5%	$E(\hat{\beta}^*)$	95%	97.5%
Constant	-0.6726	-0.4757	0.305	0.9716	1.0932	-2.3375	-1.9731	-0.312	1.1878	1.5115
Core	0.0102	0.0148	0.036**	0.0580	0.0636	0.0116	0.0151	0.037**	0.0580	0.0641
Tier1	0.0189	0.0236	0.051**	0.0823	0.0890	0.0192	0.0233	0.050**	0.0803	0.0872
Tier2	-0.0482	-0.0419	-0.016	0.0102	0.0132	-0.0475	-0.0414	-0.016	0.0094	0.0135
Div	-0.0696	-0.0251	0.178	0.3841	0.4383	-2.0148	-1.4954	1.099	3.7537	4.2784
CS	-0.1425	-0.1321	-0.092**	-0.0552	-0.0504	-0.1390	-0.1284	-0.089**	-0.0538	-0.0483
Size	-0.0183	-0.0053	0.047	0.1073	0.1210	-0.0515	-0.0240	0.094	0.2246	0.2559
Div×*Size*						-0.3139	-0.2780	-0.072	0.1293	0.1752
$\hat{\sigma}_{\varepsilon}$	0.0677	0.0708	0.089	0.1127	0.1189	0.0658	0.0687	0.087	0.1090	0.1133

Note: (1) * and ** represent the 10% and 5% levels of significance, respectively. (2) $E(\hat{\beta}^*)$ is the average of the bootstrap set with 2,000 replications.

6. Conclusions

Through the actual data analysis, we confirm the relationship between the different capital tiers of banks in the United States in regards to performance and risk. For the U.S., after moving out of the financial crisis and into the COVID-19 pandemic, all the data support that banks there should improve the core and Tier1 capital in order to reduce the impact of risk. Thus, we can reasonably infer that in the face of today's serious economic consequences caused by this health crisis, it is possible to use an appropriate capital strategy to effective control.

We adopt the two-stage bootstrapped truncated regression model proposed by Simar and Wilson (2007) to analyse the impact of Basel III capital requirements on the operational performance of U.S. commercial banks. Empirical results show significantly negative impacts when banks increase their Core or Tier 1 capital ratio, whereas an increase in the Tier 2 capital ratio has no significant impact on bank performance. The results imply that banks will prefer to increase the cheaper Tier 2 capital to meet the higher level of capital adequacy ratios, because that has no significant impact on bank performance. However, Tier 2 capital has less risk absorption capacity than Core capital and Tier 1 capital.

To prevent bank failures due to a future financial crisis, increasing Core and Tier 1 capital ratios is essential although the requirements will cause a negatively significant effect on bank performance. Therefore, raising the levels of Core and Tier 1 capital ratios gradually can diminish the negative impact on bank performance. Eventually, in the long run, a higher quality capital adequacy ratio will improve stability of the financial market and make the U.S. banking industry sounder and safer. Future studies can focus on the optimal ratio to find more favourable and direct decision points.

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