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# How are the United States Banks faring during the COVID-19 Pandemic? Evidence of Economic Efficiency Measures

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**Abstract:** Due to the current lockdown and restrictions related to the COVID-19, U.S. commercial and domestic banks are facing cashflow and financial difficulties. This has led to many vulnerable customers losing their source of income. In this paper, we examine the importance of financial liquidity and solvency on U.S. commercial and domestic banks' efficiency during the COVID-19. This paper adopts the Data Envelopment Analysis' estimator in a two-step procedure. First, economic efficiency measures of 16,830 December quarterly observations of U.S. commercial and domestic banks are estimated from December 2010 to December 2020. Within each year, 1,530 U.S. commercial and domestic banks are selected. Second, using Tobit and panel fixed effect regression models, the importance of both liquidity and solvency risks on economic efficiency during the COVID-19 is examined. Empirical estimates indicate that both liquidity and solvency financial factors negatively affect the economic efficiency measures of U.S. commercial and domestic banks during the COVID-19.

**Keywords:** COVID-19, DEA, Liquidity, Solvency

**JEL:** C01, C18, C52, Q11

## 1 Introduction

Since the identification of the Coronavirus disease (COVID-19) in China on December 2019, COVID-19 has threatened the health of people and escalated the fear factor resulting in synchronized lockdowns across the globe (Andersen et al., 2020; Bounie et al., 2020; and Zheng and Zhang, 2021). Consequently, the World Health Organization declared the COVID-19 as a global pandemic (Bounie et al., 2020; Baker et al., 2020; and Zheng and Zhang, 2021). The ongoing pandemic not only represents a worldwide public health emergency, but also has imposed massive and far-reaching economic cost globally (Baker et al., 2020 and Zheng and Zhang, 2021).[1]

In the United States (U.S.), the consensus estimates of new infections even under-estimated as some might suggest is now about 371,072 with 30,287 deaths for December $23^{rd}$, 2021 only (Figure 1).[2] With abnormal measures being put in place, such as, lockdowns, generalized teleworking, government-guaranteed loans to companies, and so on, the number of infections and loss of lives still continue to rise sharply across

1 As of June $17^{th}$, 2021 the World Health reported that the total number of confirmed COVID-19 infections worldwide was about 177,435,887 across more than 200 countries and territories, with 3,842,319 deaths.

2 The data is from the U.S Center for Disease Control and Prevention.

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the globe and particularly in U.S. Thus, the exponential increase of the number of infectious people and deaths of COVID-19 has led to a political disarray at the state's level. Furthermore, the spread of the COVID-19 and containment measures attempting to mitigate it have brought production and consumption of goods and services to a standstill (Zheng and Zhang, 2021) which has led to unprecedented public and policy concerns.

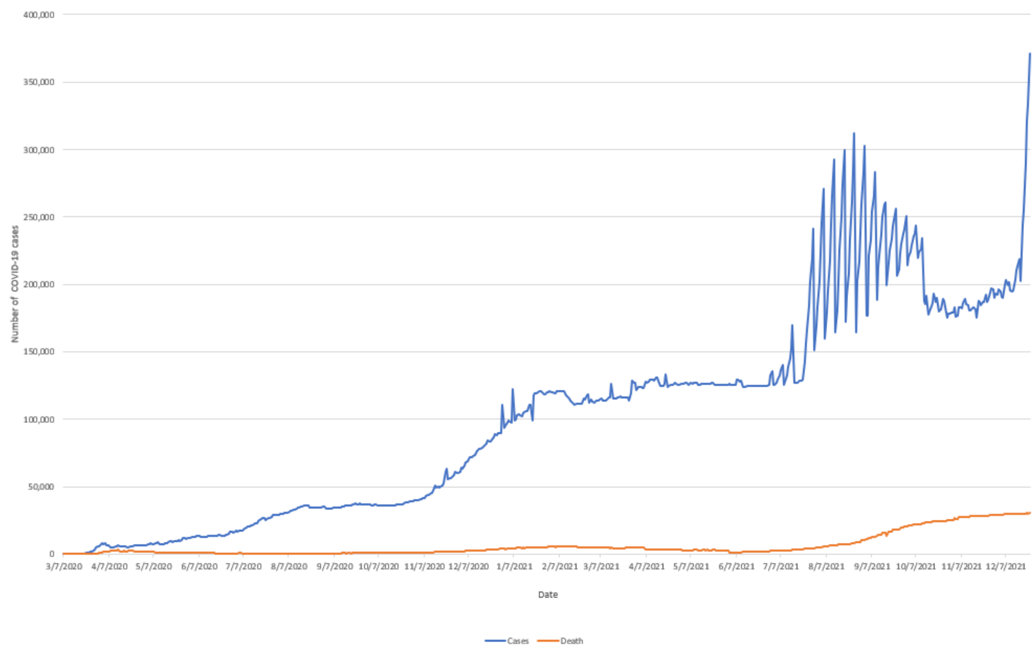


**Fig. 1.** COVID-19 Infections and death in the U.S.

Therefore, the weakened economic conditions have negatively impacted the financial system, including the banking industry. Banks, major contributors to the U.S. economy, are expected to play a key role absorbing the shock, by supplying much needed funding (Acharya and Steffen, 2020). However, because of the current pandemic, banks continue to face potential losses that can affect their capital levels and possibly lead to failure both in the short and long terms.

In the short term, the effect of the COVID-19 will likely first be seen on banks' income statements. Over the long term, if current economic conditions persist and borrowers are not able to repay their loans, banks might need to fully recognize the losses on the loans and write down the value of capital (Perkins et al., 2020). Furthermore, if repayments suddenly decline, banks can become distressed because of the likelihood of non-performing loans and the possibility in extreme cases of bank runs (Goodell, 2020). It is therefore inevitable to see enormous impacts of the COVID-19 on banking sector via its long-lasting and far-reaching effects on the U.S. overall economy (Goodell, 2020).

Overall, the great uncertainty caused by the COVID-19 is leading U.S. banking sector to become unpredictable and highly volatile via its adverse impacts on the real economy (Zhang et al., 2020). While the action of federal policy is likely to address the non-performing loans overhang during the COVID-19, the repercussions for U.S. banks are expected to last longer (Bellens et al., 2020). Thus, weak economic activity and tough employment conditions will continue to weaken the U.S. banking sector's asset quality, earnings, and solvency. Therefore, it is necessary for U.S. banks to continue playing a significant role in shaping the recovery and adapting their operating models to ensure the best efficiency measures.

The efficiency of banks is an important element of analysis and its importance on the COVID-19 has still not been addressed. Henceforth, this paper is grounded on an economic mechanism through which financial intermediaries provide bank's liquidity and solvency risks during the COVID-19. A liquidity crisis occurs when banks have their assets greater than their liabilities and are unable to provide cash in the short run. A direct consequence of the liquidity crisis during the COVID-19 is when customers withdraw their deposits at the same time, which then can lead to costly liquidation of assets and thus banks then become insolvent (Kashyap et al., 2002). A solvency crisis deals with the long run's inability of banks to provide cash (Diamond and Rajan, 2005). In this context, we aim at investigating the impact of COVID-19 on the U.S. commercial and domestic banks' efficiency measures.

In this paper, we deal with three allocative questions, focusing on the measurement of banks' efficiency measures with three unique contributions. With the rapidly growing body of research investigating the impact of the COVID-19 crisis on the macroeconomy; see for example, Baker et al., (2020), Lewis et al., (2020), and Zheng and Zhang (2021), this paper first contributes to the literature by estimating the economic efficiency measures of U.S. commercial and domestic banks during and prior to the COVID-19. Therefore, following prior studies, such as, Charnes et al., (1978); Banker et al., (1984); Wu et al., (2006); and Paradi et al., (2012); we make use of DEA technique to compute economic efficiency measures of U.S. commercial and domestic banks from December 2010 through December 2020 while accounting for the temporal (yearly) variation.

Second, we evaluate the impact of liquidity and solvency risks with banks' efficiency measures during the COVID-19 using the Tobit and panel fixed effect models to control for several heterogeneities in our data set. A thorough literature review reveals that there remains a lack of empirical evidence in the evaluation of economic efficiency measures during the COVID-19 at the U.S. regional level.

With the COVID-19 outbreaks initially concentrated in urban centres on both East and West coasts, this paper finally evaluates the impact of banks' efficiency measures on the COVID-19 across the four U.S. regions, Midwest, Northeast, South, West. Given the regional's variation in economic efficiency measures of banks, our results conclude that different banks were affected to a different degree by the COVID-19 as well as at different points in time. The remainder of this paper is structured as follows. Section 2 presents a brief literature review of the COVID-19 pandemic. Section 3 discusses the theoretical methodology. Section 4 discusses the empirical data. Section 5 details the results. Section 5 summarizes the paper and provides additional discussion.

## 2 Literature Review

The COVID-19 pandemic, a health crisis, has and is still causing unprecedented damage worldwide (Acharya and Steffen, 2020; Beck, 2020; Albanesi and Kim 2021; Béland et al. 2020; Cajner et al. 2020; Del Boca et al. 2020; Deryugina et al. 2021; Dingel and Nieman 2020; Faust et al. 2021; Fuchs-Schündeln et al. 2021; Goodell, 2020; Krieger et al. 2020; Lin et al. 2021; Mulligan, 2020; Perkins et al., 2020; and Sibley et al. 2020). While its literature is new, one particularly relevant area is the impact of COVID-19 on efficiency measures of banks. This paradigm, which was pioneered by Zheng and Zhang (2021), studies how enormous economic and social impact of COVID-19 with respect to articles that have either prognosticated such a large-scale event, and its economic consequences, or have assessed the impacts of other epidemics and pandemics.

There is a recent stream of research on the trade-off between economics and COVID-19, which has led to an important debate on how to take the most effective measures to curb the impact of the pandemic (Martínez-Córdoba et al., 2021). Buckman et al. (2020), Vinceti et al. (2020) and Eichenbaum et al. (2020) conclude that it is optimal to implement a strict lockdown for only two weeks after the first Covid-19 cases. Caulkins et al. (2021) show that it can be optimal to have two or three distinct lockdown periods, depending on local preferences regarding how to balance health and economic impacts. Atkeson et al. (2020) find that the economic benefits of rapid screening programmes exceed their costs by a ratio of 4 to 15. De Simone and Mourao (2021) find that while urban population and political stability are conducive to a prompt activation of a government's lockdown policy after initial cases, a country's wealth and the rule of law may produce an opposite effect.

Deb et al. (2020) report that school and public transport closures have a high economic cost but a limited effect on the outbreak. Chang et al. (2021) find that the high impact of cancelling public events, and on the mild impact of public transport and non-essential business closures have translated into higher unemployment. Santeramo et al. (2021) find that comprehensive lockdowns reduced the reproduction rate of COVID-19. Dave et al. (2021) show how a 'super-spreader' event in a U.S. state with a loose lockdown can impact infections in other states with more stringent measures in place. Bennett (2021) finds a significant efficiency of lockdown measures in high-income areas but non-significant in the low-income ones.

Li et al. (2021) find evidence that the impact of COVID-19 depends on time horizon with for example international travel restrictions efficient after seven days but not after 28 days. Bakker and Goncalves (2021) show that the impact of measures on infections declined over time. Russell et al. (2021) show that international travel restrictions might have little impact on pandemics except in countries with low COVID-19 incidence and large numbers of arrivals from abroad. Bakker and Goncalves (2021) find that measures have been more efficient in countries with higher government's effectiveness.

# 3 Theoretical Framework

## 3.1 Data Envelopment Analysis

The cost theory assumes that the relationship between multiple producing output quantities, $y = (y_1, y_2, \ldots, y_j) \in \mathbb{R}^J_+$, and input prices, $w = (w_1, w_2, \ldots, w_o) \in \mathbb{R}^O_+$ of input quantities, $x = (x_1, x_2, \ldots, x_o) \in \mathbb{R}^O_+$, is reflected by the concept of cost function. The cost function of an $i^{th}$ bank at time, $t$, can be defined as:

$$TC_{it} = f\left(y_{it}, w_{it}\right), \quad i = 1, 2, \ldots, N; \quad t = 1, 2, \ldots, T, \tag{1}$$

where $TC_{it}$ is the total cost of an $i^{th}$ bank at time, $t$. $y_{it}$ is the vector of output quantities of an $i^{th}$ bank at time, $t$. $w_{it}$ is the vector of input prices of an $i^{th}$ bank at time, $t$. Economic efficiency measures from equation (1) can be estimated using various estimators including: Stochastic Frontier Analysis (SFA) of Aigner et al., (1977); Data Envelopment Analysis (DEA) of Charnes et al., (1978) and Banker et al., (1984); Thick Frontier Analysis of Berger and Humphrey (1991); Distribution Free Approach of Berger (1993); Free Disposal Hull of Chang (1999); and Semi-parametric approach of Badunenko et al., (2012) and Tsionas (2017).

The estimator methods of SFA and DEA have been the two widely used approaches to modern benchmarking (Chen, 2002; Drake et al., 2006; and Sakouvogui and Shaik, 2020) while accounting for temporal variation, $t$. In dealing with the apriori knowledge of Aigner and Chu (1968)'s production function, Aigner et al., (1977) and Meeusen and Van den Broeck (1977) proposed the statistical SFA model that accounts for a composite error term consisting of inefficiency and noise components (Coelli, 1995). However, with the lack of justification of inefficiency distributions in SFA models, Charnes et al., (1978) reformed the piecewise linear convex approach of Farrell (1957) into a mathematical linear programming method referred to as, DEA.

Introduced by Charnes et al., (1978) as an alternative solution to the criticism of SFA models, DEA has become an important approach in the estimation of economic efficiency measures that are obtained as a maximum of a ratio of weighted outputs to weighted inputs (Berger and Humphrey, 1997; and Chen, 2002). The weighted ratio, determined by a restriction that the similar ratios for every bank must be less than or equal to unity, allows the efficiency measures of multiple outputs and inputs to be measured without requiring pre-assigned weights (Charnes et al., 1978).

Additionally, DEA is a nonparametric efficiency estimator that uses linear programming technique for the evaluation of economic efficiency of individual bank while requiring no prior assumption on the specification of the best practice frontier. Furthermore, DEA does not require a specific functional form to be imposed on the data in determining the efficient frontier, error, and inefficiency structures of the bank (Bauer et al., 1998). In this paper, following Färe et al., (1985) and Sakouvogui et al.,(2020), the cost minimization DEA model of an $i^{th}$ bank can be defined as:

$$\begin{aligned} \varpi = & \underset{\lambda, x_o}{\text{minimize}} \quad w_i^o x^{\star o} \\ & \text{subject to} \quad \sum_{i=1}^{n} \lambda^i y^{jo} \geq y^j, \ j = 1, \ldots, J, \\ & \sum_{i=1}^{n} \lambda^i x^{oi} \leq x^{\star o}, \ for \quad \forall o, \\ & \lambda^i > 0, \ for \quad \forall \lambda^i, \end{aligned} \tag{2}$$

where $i = 1, \ldots, n$ measures the number of banks. $o = 1, \ldots, O$ measures the number of inputs. $j = 1, \ldots, J$ measures the number of output quantities. $x_o^\star$ is the cost minimizing vector of input quantities for the evaluated bank, given the vector of input prices, $w_o$, and output quantities, $y_j$.

In the literature, two scale assumptions are generally employed, constant returns-to-scale and variable returns-to-scale. Equation 2 represents the constant returns-to-scale. The convexity constraint implies that an inefficient bank is benchmarked against banks of a similar size and therefore the projected point of that bank on the DEA frontier will be a convex combination of the observed banks (Romzie et al., 2014). Therefore, in accounting for the variable returns-to-scale's convexity condition for the weight, $\lambda^i$, the constraint of equation 2, then becomes $\sum_{j=1}^{n} \lambda^i$=1. Furthermore, to avoid bias of scale due to the economic efficiency measures, the scale efficiency measures, computed as the ratio of economic efficiency measures under constant returns-to-scale over pure technology estimated under variable returns-to-scale, are estimated.

With the evaluation of economic efficiency measures on liquidity and solvency risks during the COVID-19, a two-step approach is employed. In the first step, the economic efficiency measures of banks are estimated using equation 2. In the second step, using the Tobit regression model, the impact of economic efficiency measures on liquidity and solvency risks during the COVID-19 is evaluated.[3]

## 3.2 Tobit Regression model

The Tobit regression, used in the second step, is an appropriate tool to be used because the cost efficiency measures obtained from equation (2) are censored and cannot exceed 1 nor be below 0. The Tobit regression model of Tobin (1958) can be expressed as:

$$\begin{aligned} u_{it}^\star &= \delta\theta_{it} + \epsilon_{it} \\ \text{subject to} \quad u_{it} &= u_{it}^\star \quad if \quad u_{it}^\star \in [a, b] \\ u_{it} &= a \quad if \quad u_{it}^\star \leq a \\ u_{it} &= b \quad if \quad u_{it}^\star \geq b \end{aligned} \tag{3}$$

where $u_{it}$ is the economic inefficiency measures, which is defined by a latent variable $u_{it}^\star$ for positive values of the inefficiency measures and censored otherwise. $\delta$ is a vector of estimated parameters. $\theta_{it}$ is a vector of explanatory variables of an $i^{th}$ bank at time, $t$. $\varepsilon_{it}$ is a random variable that captures the effect of the unobserved factors of an $i^{th}$ bank at time, $t$, and distributed with zero mean and constant variance, $\sigma^2$. a is the lower limit and b is the upper limit of the dependent variable.

3 In the theoretical framework and following Pasiouras et al. 2009, the Tobit model is first used to evaluate the impact of exogenous variables on the cost efficiency measures. However, we additionally perform the robustness analysis using the panel fixed effect estimator to test for endogeneity between the financial factors of liquidity and solvency risks and the cost efficiency measures.

# 4 Empirical Data

This paper uses a total of over 16,830 December quarterly observations of U.S. commercial and domestic banks, selected from a period of 2010 to 2020. Within each year spanning from December 2010 to December 2020, 1,530 banks are selected.[4] In the selection of output quantities and input prices pertinent to the estimation of economic efficiency measures, we follow the intermediate approach presented in Pessarossi and Weill (2015), Sakouvogui and Shaik (2020) and Sakouvogui (2020b), and thus suggesting that banks collect deposits to transform them into loans and capital.

Two output quantities are selected, total loans, $y_1$, and other earning assets, $y_2$, with three input prices, price of labor, $w_1$, price of physical capital, $w_2$, and price of borrowed funds, $w_3$. The dependent variable, total cost, $TC$, is calculated as the sum of interest expenses, personnel expenses, and other operating expenses. We additionally impose homogeneity condition by respectively normalizing, $TC$, $w_1$ and $w_2$ by $w_3$. Following Sakouvogui and Shaik (2020) and Sakouvogui (2020a), the definitions of variables are in Table 1.

**Table 1.** Variables definitions

| Variables | Formula | Definitions |
|---|---|---|
| Price of labor, $w_1$ | $\frac{\textit{Personnel expenses}}{\textit{Total assets}}$ | Price of labor is the price associated with the sum of all wages paid to employees, as well as the price of employee benefits. Personnel expenses include salaries and employee benefits. Total asset is the sum of total loans and leases, total held-to-maturity securities, total available-for-sale securities, trading assets, total intangible assets, other real estate owned, all other assets minus allowance for loan and lease losses. |
| Price of physical capital, $w_2$ | $\frac{\textit{Other operating expenses}}{\textit{Fixed assets}}$ | Price of physical capital is the price of maintaining building. Other operating expenses is the sum of Goodwill impairment losses, amortization expenses and impairment losses for other intangible assets. Fixed assets are assets which are purchased for long-term use and unlikely to be quickly converted into cash |
| Price of borrowed funds, $w_3$ | $\frac{\textit{Interest expenses}}{\textit{Total deposits}}$ | Price of borrowed funds is the price of associated with borrowing money. Total interest expense is the sum of the interest expense. Total deposit is the sum of all domestic deposits including demand, saving and fixed deposits minus noninterest bearing and interest bearing |
| Total loans, $y_1$ | | Sum of all type of loans including: loans secured by real estate, agricultural production and other farmers, commercial real estate, construction and land development activities, individuals for household, family, and other personal expenditures, individuals for households, family, and other personal expenditures: credit cards and other construction. |
| Other earning assets, $y_2$ | | Other earning assets consists of balances due from the bank, inter-bank loans, investments, and securities. Other earning assets consists of balances due from the bank, inter-bank loans, investments, and securities. |
| Total cost, TC | | Sum of interest expenses, personnel expenses, and other operating expenses. |
| Liquidity , *Liq* | $\frac{\textit{Liquid assets}}{\textit{Total deposits}}$ | Liquidity risk is the ability to quickly rise cash. The liquidity measures in this paper follows the works of Kashyap and Stein (2000) and Aspachs et. (2005), and Moore (2010). This measure informs on the split between liquid and illiquid assets on the balance sheet (Aspachs et al. 2005), and provides information about the liquidity shock absorption capacity of banks and ignores the flow of funds from repayment, increases in liabilities and the demand for banks funds (Moore 2010). |
| Solvency | $\frac{\textit{Total equity}}{\textit{Total assets}}$ | Capacity to face difficulties during the downturn. Ghosh (2016) suggests that well-capitalized banks are relatively safer and less risky and thus, we expect well-capitalized banks to serve as a constraining mechanism on the loss of economic efficiency measures in banking (Adeabah and Andoh, 2020) |
| Bank's Size, *Size* | Log of total assets | Bank's Size is measured by the natural logarithm of total amount of assets owned by the bank. |
| COVID-19 | 1 if year=2020 and 0 otherwise. | In terms of the regression models, COVID-19 is a dummy variable. In my view, I can not employ the COVID-19 cases or death rate because I believe that the consensus estimates of new infections is bias (either under-estimated or over-estimated). |

Table 2 presents the summary statistics, mean, standard deviation, minimum, and maximum, of bank-specific and economic variables of a panel data of 16,830 December quarterly observations of U.S. commercial and domestic banks ranging from 2010 through 2020. Furthermore, to reduce the effect of possibly spurious outliers, the variables are logathorised in Table 2.

## 4.1 Empirical Model and Robustness

Following prior studies, such as, Sakouvogui and Shaik (2020), the baseline Tobit specification with heteroscedasticity robust standard errors at bank level is presented by equation (3) to respectively account for

4 The data is from the Federal Financial Institutions Examination Council based on the Council Form 041 Report of Condition and Income of U.S. commercial and domestic banks that report to the Federal Reserve Board. https://cdr.ffiec.gov/public/PWS/DownloadBulkData.aspx. The quarterly data for December would include the previous 3 quarters data, quarter 1: January $1^{st}$ to March $31^{st}$, quarter 2: April $1^{st}$ to June $31^{st}$, quarter 3: July $1^{st}$ to September $31^{st}$ and quarter 4: October $1^{st}$ to December $31^{st}$. The physical year starts with January $1^{st}$ and ends with December $31^{st}$, of each year. But keep in mind, each bank has 30 days after the quarter ends to submit their call reports.

**Table 2.** Summary statistics of input and output variables

| Variable | Mean | Std.dev | Minimum | Maximum |
|---|---|---|---|---|
| | Input prices and Output quantities | | | |
| Total cost | 15.909 | 1.463 | 10.919 | 20.706 |
| Price of labor | 0.797 | 0.888 | -4.667 | 3.953 |
| Price of physical capital | 1.296 | 1.69 | -4.522 | 11.094 |
| Total loans | 7.711 | 1.953 | 0 | 13.66 |
| Other earning assets | 11.162 | 1.388 | 5.855 | 14.167 |
| | Covariates of the Regression model | | | |
| Liquidity | -8.223 | 1.086 | -17.982 | -3.085 |
| Bank's size | 14.708 | 1.251 | 10.171 | 17.538 |
| Solvency | -2.26 | 0.267 | -4.407 | -1.313 |

Mean: overall mean. std.dev: standard deviation. The total number of observations is 16,830. Within each year, 1530 banks were selected.

the exogenous variables of an $i^{th}$ bank at time, $t$, as:

$$\begin{aligned} u_{it}^{\star} &= \delta_0 + \delta_1 COVID + \delta_2 \ln(Liq_{it}) + \delta_3 COVID \times \ln(Liq_{it}) \\ &\quad + \delta_4 \ln(Sol_{it}) + \delta_5 COVID \times \ln(Sol_{it}) + \delta_6 \ln(size_{it}) + \epsilon_{it} \end{aligned} \tag{4}$$

for $i = 1, .., n$ and $t = 1, ..,T$. $\delta_0$ is the intercept. $\delta_1$ is the estimated parameter of COVID-19. $\delta_2$ is the estimated parameter of liquidity risk. $\delta_3$ is the estimated parameter of the interaction between COVID-19 and liquidity risk. $\delta_4$ is the estimated parameter of solvency risk. $\delta_5$ is the estimated parameters of the interaction between COVID-19 and solvency risk. $\delta_6$ is the estimated parameter of bank's size. $\epsilon_{it}$ is the random error.

The suitability of the Tobit regression model (equation 4) is not justified by the distributional heterogeneity issue of Shapiro-Wilk test. Consequently, following Sakouvogui (2020b), the Tobit model fails to account for the unobserved bank-specific fixed effect, and thus the application of the fixed effect is appropriate to meet the test requirement for endogeneity between economic efficiency measures and exogeneous variables.[5] Therefore, the panel fixed effect model is specified as follows:

$$\begin{aligned} u_{it} &= \alpha_i + \delta_1 COVID + \delta_2 \ln(Liq_{it}) + \delta_3 COVID \times \ln(Liq_{it}) \\ &\quad + \delta_4 \ln(Sol_{it}) + \delta_5 COVID \times \ln(Sol_{it}) + \delta_6 \ln(size_{it}) + \mu_{it} \end{aligned} \tag{5}$$

for $i = 1, .., n$ and $t = 1, ..,T$. $\alpha_i$ is the observed bank-specific effect. $\delta_1$ is the estimated parameter of COVID-19. $\delta_2$ is the estimated parameter of liquidity risk. $\delta_3$ is the estimated parameter of the interaction between COVID-19 and liquidity risk. $\delta_4$ is the estimated parameter of solvency risk. $\delta_5$ is the estimated parameters of the interaction between COVID-19 and solvency risk. $\delta_6$ is the estimated parameter of bank's size. $\mu_{it}$ is the random error.

# 5 Empirical Results

## 5.1 Distribution of Economic Efficiency Measures

In this paper, using the input-oriented DEA model in equation (2), economic efficiency measures (under CRS, VRS, and scale assumptions) are estimated while accounting for the yearly variability and thus, for the technological changes[6]. The scale economic efficiency of banks is calculated by taking the ratio of the CRS to

5 The fixed effect model was selected based on its relevance to the data set used for this analysis. Shapiro-Wilk test of normality is rejected at the 1% significance level.

6 The yearly estimation of economic efficiency measures is used to account for the sensitivity to sample heterogeneity in the DEA model

the VRS efficiency ratings. Table 3 presents the summary statistics of the DEA economic efficiency measures. From Table 3, three important results emerge.

First, the minimum and maximum economic efficiency measures of the DEA model under CRS, VRS, and scale assumptions are high (their respective histograms presented in Figures 2, 3 and 4). This is expected due to the lack of random noise in the DEA model and thus, any deviation from the estimated frontier is interpreted as being due to inefficiency. These results confirm the trend found in Sakouvogui and Shaik (2020) and Sakouvogui (2020b) and the suggestion that banks are generally efficient, which are consistent with other recent studies; see for example, Berger and Humphrey (1997), Pasiouras et al., (2009), Sakouvogui and Shaik (2020), and Sakouvogui (2020b).

Second, the results show that the mean economic efficiency measures are not stable over time (fluctuate slightly throughout the years). The yearly average of efficiency measures ranges between 0.8020 to 1.000 under CRS assumption, 0.8763 to 1.000 under VRS assumption and 0.8981 to 1.000 under scale assumption. However, the results of Table 3 should be investigated with care, while general results, related to the performance of the whole year, are consistent. Furthermore, in looking into the mean and standard deviations of economic efficiency measures, we can conclude that the performance of banks does show a statistically significant change over time, specifically in 2020. That is, during the latter part of the COVID-19 in 2020, the average economic efficiency measures of the DEA model under CRS, VRS, and scale assumptions decrease.

Third, the results of our analysis show that within each year, there exists a large variation between the minimum economic efficiency measures and the average economic efficiency measures. For example, the mean efficiency measures of the DEA model under CRS assumption is 0.8117 with a standard deviation of 0.058, and thus indicating that most of the banks have efficiency scores falling between 0.7537 and 0.8697. For the DEA model under the VRS assumption, the mean efficiency measure is 0.8921 and a standard deviation of 0.0454. Thus, under the VRS assumption of the DEA model, most of the banks have efficiency measures falling between 0.8467 and 0.9375. And finally, with the DEA model under the scale assumption, with a pooled efficiency measure of 0.9097 and a standard deviation of 0.0393, most of the banks have efficiency measures falling between 0.8704 and 0.9490. Finally, the pooled efficiency measures of the DEA model are respectively 81.17 percent, 89.21 percent and 90.97 percent under CRS, VRS, and scale assumptions. Furthermore, a comparison of the ratio suggests that VRS technology overestimates on average and this is suggested by the scale efficiency measures.

Furthermore, to gain a more accurate perspective on the size-efficiency relationship, the DEA's economic efficiency measures under the scale assumption are used in the evaluation of liquidity and solvency risks during the COVID-19. Thus, the Tobit and panel fixed effect regression models with heterogeneity (equations 4 and 5) are estimated with the parameter estimates presented in Table 4.

The results in Table 4 reveal the negative effect of the COVID-19 on the economic efficiency measures. This negative effect can be viewed in two dimensions. First, during the pandemic, health improvements are meant to decrease banking efficiency of either output or input. Thus, prior to pandemic technological improvements in the banking sector aided in improved production. These normally lead to higher profit. And second, the statistically significant and negative impact of COVID-19 suggest lower economic efficiency measures. These findings are consistent across both Tobit and fixed effect regression models. The significant negative impact of COVID-19 on economic efficiency measures under the DEA model follows the recent literature that suggests that a pandemic-induced economic downturn will put pressure on banks' loan portfolios and can lead to a large withdrawal of deposits (Lagoarde-Segot and Leoni, 2013 and Zheng and Zhang, 2021). Therefore, one could expect that the COVID-19 to deliver a negative effect on banks efficiency measures by the deterioration in performance of small and medium-sized banks, a strong decline in economic activity (Skoufias, 2003) and excessive build-up of non-performing loans (Zheng and Zhang, 2021).

The well-being of an economy depends largely on the performance of its banking sector. Banks play an important role in the daily financial system of a country and specially during the pandemic. It can be shown that during the pandemic crisis, U.S. commercial and domestic banks fail to perform the two most central roles of the modern theory of the financial intermediation: 1) create liquidity in the short run, 2) be solvent in long run (Berger and Bouwman, 2009). From Table 4, we observe that liquidity and solvency risks are both positive and significant at a 1 percent significance level across both the Tobit and fixed effect models. The

**Table 3.** Summary of economic efficiency measures

| Year | Mean | Std.dev | Minimum | Maximum | Year | Mean | Std.dev | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|---|
| | | | | CRS assumption | | | | | |
| 2010 | 0.8363 | 0.0649 | 0.7049 | 1.0000 | 2016 | 0.802 | 0.0534 | 0.7209 | 1.0000 |
| 2011 | 0.8198 | 0.0674 | 0.7055 | 1.0000 | 2017 | 0.8077 | 0.0556 | 0.7208 | 1.0000 |
| 2012 | 0.8093 | 0.0631 | 0.6978 | 1.0000 | 2018 | 0.8074 | 0.0528 | 0.7275 | 1.0000 |
| 2013 | 0.8071 | 0.0585 | 0.7161 | 1.0000 | 2019 | 0.8178 | 0.0525 | 0.7406 | 0.9799 |
| 2014 | 0.8044 | 0.0522 | 0.7241 | 1.0000 | 2020 | 0.8109 | 0.0545 | 0.7283 | 1.0000 |
| 2015 | 0.8061 | 0.0544 | 0.7263 | 0.9875 | Pooled | 0.8117 | 0.058 | 0.6978 | 1.0000 |
| | | | | VRS assumption | | | | | |
| 2010 | 0.8947 | 0.0474 | 0.781 | 1.0000 | 2016 | 0.8932 | 0.0468 | 0.77 | 1.0000 |
| 2011 | 0.8804 | 0.0497 | 0.7931 | 1.0000 | 2017 | 0.9006 | 0.043 | 0.8368 | 1.0000 |
| 2012 | 0.8763 | 0.049 | 0.7551 | 1.0000 | 2018 | 0.8977 | 0.0397 | 0.8269 | 1.0000 |
| 2013 | 0.882 | 0.0452 | 0.7963 | 1.0000 | 2019 | 0.9047 | 0.0403 | 0.8299 | 1.0000 |
| 2014 | 0.8875 | 0.0421 | 0.8042 | 1.0000 | 2020 | 0.9017 | 0.0432 | 0.8257 | 1.0000 |
| 2015 | 0.8941 | 0.0436 | 0.7894 | 1.0000 | Pooled | 0.8921 | 0.0454 | 0.7551 | 1.0000 |
| | | | | Scale assumption | | | | | |
| 2010 | 0.9339 | 0.0319 | 0.8625 | 1.0000 | 2016 | 0.8981 | 0.0396 | 0.7948 | 1.0000 |
| 2011 | 0.9302 | 0.0333 | 0.8418 | 1.0000 | 2017 | 0.8968 | 0.0412 | 0.8007 | 1.0000 |
| 2012 | 0.9229 | 0.0334 | 0.8319 | 1.0000 | 2018 | 0.8993 | 0.0398 | 0.8001 | 1.0000 |
| 2013 | 0.9146 | 0.0356 | 0.8183 | 1.0000 | 2019 | 0.9039 | 0.0378 | 0.7975 | 0.9983 |
| 2014 | 0.9064 | 0.0373 | 0.8169 | 1.0000 | 2020 | 0.8993 | 0.0403 | 0.7744 | 1.0000 |
| 2015 | 0.9014 | 0.0384 | 0.8084 | 0.9994 | Pooled | 0.9097 | 0.0393 | 0.7744 | 1.0000 |

Within year, the total number of banks is 1,530. Year: time of economic efficiency measures. Pooled: overall mean of economic efficiency measures. std.dev: standard deviation of economic efficiency measures. Minimum: minimum economic efficiency measures over time. Maximum: maximum economic efficiency measures over time.

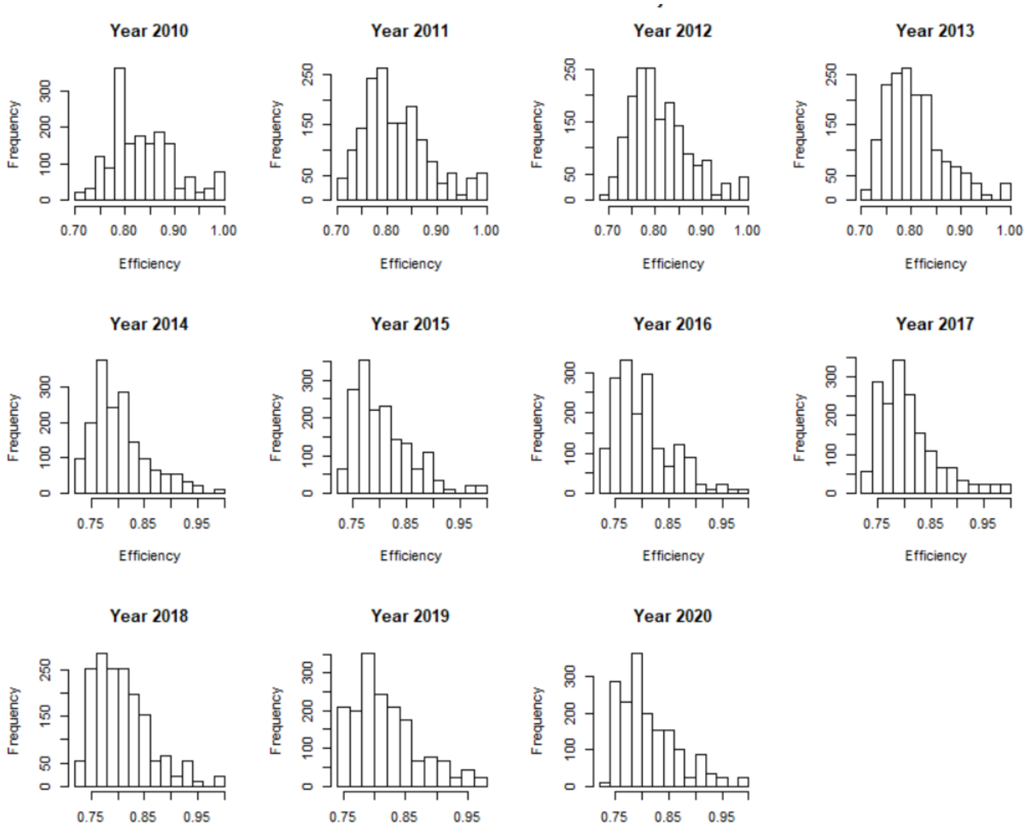


**Fig. 2.** Economic efficiency measures under CRS assumption

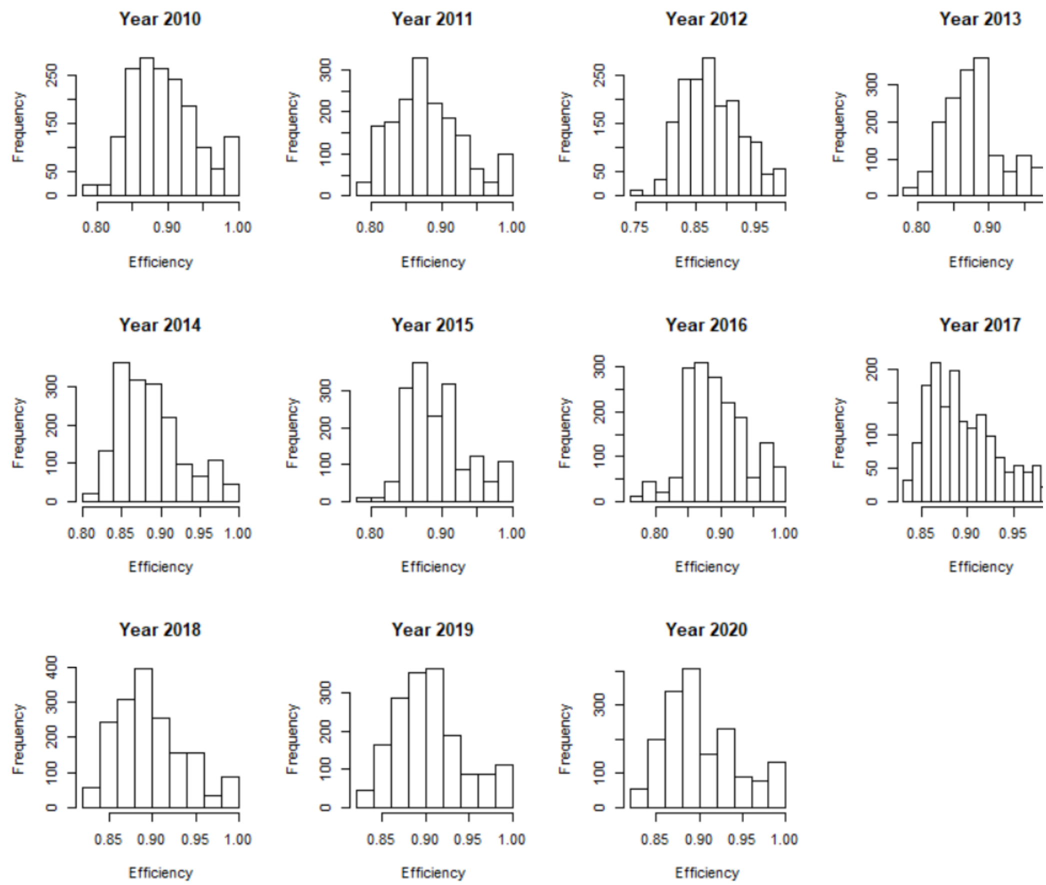


**Fig. 3.** Economic efficiency measures under VRS assumption

results of the liquidity risk indicate that increasing the ratio of liquid assets to that of deposits positively impact the economic efficiency measures and thus suggesting that greater liquidity is associated with greater efficiency gain. This is consistent with the finding of Kashyap et al., 2002; Repullo, 2003; Aspachs et al., 2005; and Mcmillan and Mcmillan, 2017. Concerning solvency, the results suggest that high capital requirements increase the economic efficiency of U.S. banks. Hence, U.S. banks get more efficient as they increase their capital.

Studies have shown that a banking crisis provides disruptive effects on the real economy (Aspachs et al., 2005). Consequently, it is essential and thus important to identify how liquidity and solvency risks may have contributed to the banking efficiency measures during the COVID-19. Therefore, from Table 4, we observe that the parameter estimates of the interaction terms, liquidity risk × COVID-19 and solvency risk × COVID-19, are respectively and negatively related to the economic efficiency measures of banks, and thus indicating a downturn in the U.S. banking sector during the COVID-19. That is, U.S. commercial and domestic banks are better positioned to support the lending needs of the real economy because of the aggressive interventions of the Federal Reserve and U.S. Treasury Department which encouraged them to continue providing credit, in some cases by incentivizing them to draw down their buffers (Demirguc-Kunt et al., 2020).

Furthermore, during the COVID-19, one observes two trends: (1) increased savings (input) because people made less consumption or because people became more precautious and (2) reduced loan issuance (output) because U.S. commercial and domestic banks tended to curb new credit when they perceive economic downturn is upcoming. The observed trends for savings and loans were well justified in my view but they negatively impacted the economic efficiency measures of U.S. commercial and domestic banks. Therefore, weak economic activity did weaken the U.S. banking sector's asset liquidity and solvency. While this time, U.S.

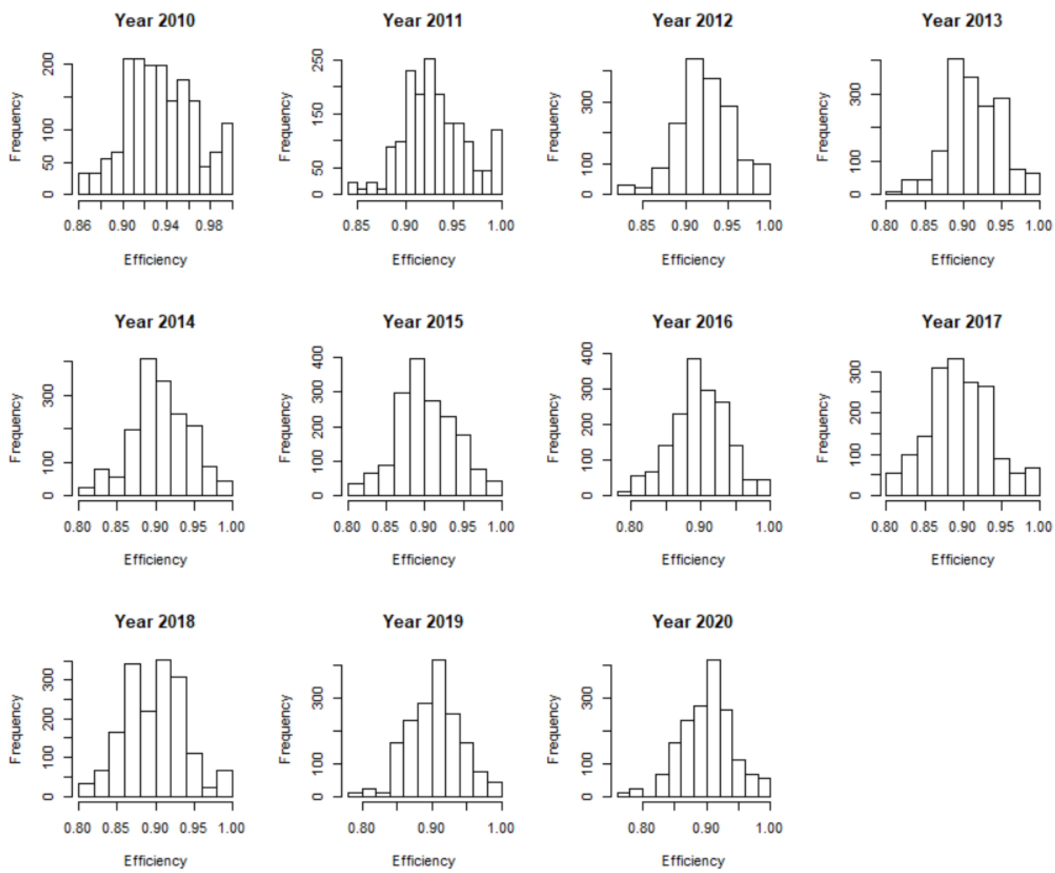


**Fig. 4.** Economic efficiency measures under scale assumption

commercial and domestic banks appear to be part of the solution to the COVID-19 crisis, the banking sector has also been hit hard by a rapid increase in the amount of credit losses and an extended uncertainty on the credit environment and duration of the crisis (Demirguc-Kunt et al., 2020).

**Table 4.** Impact of COVID-19 on economic efficiency measures

| Parameter | Tobit Model | | Fixed Effect Model | |
|---|---|---|---|---|
| | Estimate | Standard Error | Estimate | Standard Error |
| Intercept | 1.03970*** | 0.04089 | 0.94630*** | 0.01663 |
| *COVID − 19* | -0.09342** | 0.04072 | -0.09342** | 0.04081 |
| *Liquidity* | 0.00264 | 0.00257 | 0.00133 | 0.00098 |
| *Liquidity × COVID − 19* | -0.00131* | 0.00275 | -0.00131* | 0.00275 |
| *solvency* | 0.03464* | 0.01469 | -0.00905* | 0.00370 |
| *solvency × Covid − 19* | -0.04368*** | 0.01515 | -0.04368*** | 0.01518 |
| Bank's size | -0.00307*** | 0.00077 | -0.00307*** | 0.00077 |
| $\sigma$ | 0.03884*** | 0.00067 | | |
| **Performance** | | | | |
| LogLikelihood | 3077.00 | | 3040.95 | |
| AIC | -6138.00 | | -6079.90 | |
| BIC | -6095.00 | | -6074.50 | |

The AIC and BIC can be used to compare nested and non-nested models. $\sigma$ is equivalent to the square root of the residual variance in Tobit regression. Standard Error values are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

## 5.2 U.S. Census Bureau-designated regions

To gain further insight into the relationship between COVID-19 and economic efficiency measures, we now present the results of the economic efficiency measures within the four U.S. regional classification, Midwest, Northeast, South, and West. Tables 5, 6, and 7 summarize the results of economic efficiency measures using an input-oriented DEA model under CRS, VRS, and scale assumptions.

The results of the economic efficiency measures in Tables 5, 6, and 7 indicate that the majority of U.S. commercial and domestic banks operate at constant returns to scale and the scale inefficiency increases with bank's size, and thus affecting rationalization of the input combination needed to reach their most productive scale sizes. Furthermore, when the U.S. commercial and domestic banks are split out by geographic region, significant differences in performance are noted, and these correlates well with the actual economic climate in such regions.

Nevertheless, the results of Tables 5, 6, and 7 suggest that the average economic efficiency measures of the U.S. commercial and domestic banks have failed to achieve a fully efficient status. Thus, this performance could be a sign of stellar function in the U.S. banking sector, particularly during the COVID-19. In accounting for the results of the economic efficiency measures under the scale assumption in Table 7, we can see that the most efficient region among Midwest, Northeast, South and West, is Midwest. However, it is important to keep in mind that all regions exhibit the utmost efficiency.

In investigating the economic efficiency measures in Midwest, we observe that it produces and commercializes agricultural innovations in an efficient manner throughout our examination period. Furthermore, Midwest seems to be the region where the most suitable mix of inputs combines to produce the desirable innovative outputs. Henceforth, U.S. commercial and domestic banks in the Midwest should be set as examples and benchmarks for policymakers to determine the factors that led them to this success in terms of efficiency measures during the COVID-19. We should note that the success of Midwest does not lie solely to the fact that U.S. commercial and domestic banks showed top performances at one point in time, but mainly because they managed to keep their performances at the same level throughout the whole period undertaking in our paper.[7]

In this paper, we believe that it is additionally crucial to evaluate how the impact of COVID-19 on economic efficiency measures within the U.S. regions has evolved through time. A rise of the mean efficiency measures throughout the Midwest region could indicate that U.S. commercial and domestic banks become more efficient through the adaptation of better customer success procedures, improvement of the technology and/or the better combination of the innovative resources, such as, agriculture's land development. Table 8 reports the results of Tobit and fixed effect regression models for the evaluation of COVID-19 on economic efficiency measures within Midwest, Northeast, West and South regions. The cross-sectional result by region shows contrasting results between U.S. commercial and domestic banks in northeastern areas and in other areas.

From Table 8, the established negative effect of the COVID-19 on economic efficiency measures is consistent across Midwest, South, and West regions for the Tobit and fixed effect regression models. The negative sign of the COVID-19 implies that the economic efficiency of the U.S. commercial and domestic banks decrease across Midwest, South, and West regions. However, for the Northeast region, we have reservations about the sign of the COVID-19, and interaction between COVID-19 and liquidity risk and between COVID-19 and solvency risk. This can only distort the desperately needed interpretation of the positive parameter estimate of the COVID-19 using the Tobit and panel fixed regression models by the researcher at large; unsound advice can be very damaging on several levels. This positive estimate of the COVID-19 in the Northeast region is not reflective of the other three regions. That is, the northeastern U.S. commercial and domestic banks are better at dealing with negative shocks.

Furthermore, the coefficients of the interaction terms, COVID-19 × liquidity and COVID-19 × solvency, are negative and statistically insignificant in the Tobit model. This indicates that the positive effect of liquidity

7 The results of the banks performing in the top tiers (or if possible, lower tiers included) of efficiency for each of the regions can be available to the readers if requested.

**Table 5.** Regional economic efficiency measures under CRS assumption

| Year | Mean | Std.dev | Minimum | Maximum | Year | Mean | Std.dev | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Midwest Region | | | | |
| 2010 | 0.8560 | 0.0660 | 0.7420 | 1.0000 | 2016 | 0.8130 | 0.0550 | 0.7210 | 0.9620 |
| 2011 | 0.8350 | 0.0670 | 0.7060 | 0.9970 | 2017 | 0.8210 | 0.0570 | 0.7420 | 0.9920 |
| 2012 | 0.8240 | 0.0640 | 0.6980 | 1.0000 | 2018 | 0.8240 | 0.0550 | 0.7330 | 1.0000 |
| 2013 | 0.8210 | 0.0590 | 0.7270 | 1.0000 | 2019 | 0.8290 | 0.0530 | 0.7480 | 0.9770 |
| 2014 | 0.8170 | 0.0560 | 0.7240 | 1.0000 | 2020 | 0.8230 | 0.0550 | 0.7450 | 1.0000 |
| 2015 | 0.8190 | 0.0550 | 0.7350 | 0.9870 | Pooled | 0.8260 | 0.0590 | 0.6980 | 1.0000 |
| | | | | | Northeast Region | | | | |
| 2010 | 0.8270 | 0.0570 | 0.7280 | 1.0000 | 2016 | 0.7910 | 0.0530 | 0.7360 | 1.0000 |
| 2011 | 0.8060 | 0.0450 | 0.7330 | 0.8990 | 2017 | 0.7910 | 0.0360 | 0.7360 | 0.8710 |
| 2012 | 0.7910 | 0.0430 | 0.7320 | 0.9130 | 2018 | 0.7910 | 0.0340 | 0.7330 | 0.8620 |
| 2013 | 0.7890 | 0.0430 | 0.7250 | 0.9230 | 2019 | 0.8160 | 0.0500 | 0.7410 | 0.9590 |
| 2014 | 0.7900 | 0.0470 | 0.7350 | 0.9470 | 2020 | 0.8000 | 0.0500 | 0.7280 | 0.9390 |
| 2015 | 0.7960 | 0.0550 | 0.7350 | 0.9750 | Pooled | 0.7990 | 0.0480 | 0.7250 | 1.0000 |
| | | | | | South Region | | | | |
| 2010 | 0.8250 | 0.0610 | 0.7170 | 1.0000 | 2016 | 0.7960 | 0.0480 | 0.7220 | 0.9120 |
| 2011 | 0.8150 | 0.0730 | 0.7170 | 1.0000 | 2017 | 0.8050 | 0.0610 | 0.7210 | 1.0000 |
| 2012 | 0.8050 | 0.0660 | 0.7130 | 0.9970 | 2018 | 0.7980 | 0.0530 | 0.7360 | 1.0000 |
| 2013 | 0.8020 | 0.0580 | 0.7160 | 0.9570 | 2019 | 0.8080 | 0.0470 | 0.7460 | 0.9800 |
| 2014 | 0.7980 | 0.0480 | 0.7270 | 0.9400 | 2020 | 0.8020 | 0.0530 | 0.7440 | 0.9980 |
| 2015 | 0.7980 | 0.0500 | 0.7260 | 0.9700 | Pooled | 0.8050 | 0.0570 | 0.7130 | 1.0000 |
| | | | | | West Region | | | | |
| 2010 | 0.7990 | 0.0680 | 0.7050 | 0.9240 | 2016 | 0.7990 | 0.064 | 0.7400 | 0.9510 |
| 2011 | 0.7960 | 0.0830 | 0.7110 | 1.0000 | 2017 | 0.7970 | 0.057 | 0.7330 | 0.9310 |
| 2012 | 0.7960 | 0.0800 | 0.7200 | 0.9870 | 2018 | 0.7990 | 0.062 | 0.7280 | 0.9300 |
| 2013 | 0.8000 | 0.0770 | 0.7310 | 1.0000 | 2019 | 0.8030 | 0.069 | 0.7420 | 0.9330 |
| 2014 | 0.8000 | 0.0550 | 0.7500 | 0.9020 | 2020 | 0.8100 | 0.063 | 0.7450 | 0.9160 |
| 2015 | 0.7970 | 0.0580 | 0.7350 | 0.8980 | Pooled | 0.8000 | 0.065 | 0.7050 | 1.0000 |

Year: time of economic efficiency measures. Pooled: overall mean of economic efficiency measures. std.dev: standard deviation of economic efficiency measures. Minimum: minimum economic efficiency measures over time. Maximum: maximum economic efficiency measures over time.

**Table 6.** Regional economic efficiency measures under VRS ssumption

| Year | Mean | Std.dev | Minimum | Maximum | Year | Mean | Std.dev | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Midwest Region | | | | |
| 2010 | 0.9070 | 0.0490 | 0.8180 | 1.000 | 2016 | 0.8900 | 0.0510 | 0.7700 | 0.9920 |
| 2011 | 0.8880 | 0.0510 | 0.7970 | 0.997 | 2017 | 0.8980 | 0.0430 | 0.8390 | 1.0000 |
| 2012 | 0.8830 | 0.0510 | 0.7550 | 1.000 | 2018 | 0.8980 | 0.0400 | 0.8270 | 1.0000 |
| 2013 | 0.8870 | 0.0490 | 0.7960 | 1.000 | 2019 | 0.9020 | 0.0420 | 0.8300 | 1.0000 |
| 2014 | 0.8890 | 0.0470 | 0.8040 | 1.000 | 2020 | 0.8990 | 0.0430 | 0.8340 | 1.0000 |
| 2015 | 0.896 | 0.0490 | 0.7890 | 1.000 | Pooled | 0.8940 | 0.0470 | 0.7550 | 1.0000 |
| | | | | | Northeast Region | | | | |
| 2010 | 0.8950 | 0.0420 | 0.8300 | 1.000 | 2016 | 0.8860 | 0.0410 | 0.8320 | 1.0000 |
| 2011 | 0.8780 | 0.0330 | 0.8240 | 0.954 | 2017 | 0.8920 | 0.0360 | 0.8380 | 1.0000 |
| 2012 | 0.8660 | 0.0340 | 0.8090 | 0.940 | 2018 | 0.8890 | 0.0270 | 0.8390 | 0.9420 |
| 2013 | 0.8720 | 0.0320 | 0.8200 | 0.945 | 2019 | 0.9060 | 0.0390 | 0.8350 | 1.0000 |
| 2014 | 0.8780 | 0.0310 | 0.8270 | 0.960 | 2020 | 0.8940 | 0.0420 | 0.8260 | 1.0000 |
| 2015 | 0.8850 | 0.035 | 0.8400 | 0.980 | Pooled | 0.8860 | 0.0370 | 0.8090 | 1.0000 |
| | | | | | South Region | | | | |
| 2010 | 0.8860 | 0.0430 | 0.8060 | 1.000 | 2016 | 0.8940 | 0.0420 | 0.8060 | 0.9820 |
| 2011 | 0.8770 | 0.0530 | 0.8030 | 1.000 | 2017 | 0.9020 | 0.0460 | 0.8370 | 1.0000 |
| 2012 | 0.8750 | 0.0530 | 0.7900 | 0.998 | 2018 | 0.8960 | 0.0420 | 0.8330 | 1.0000 |
| 2013 | 0.8800 | 0.0460 | 0.7970 | 0.989 | 2019 | 0.9030 | 0.0360 | 0.8520 | 0.9930 |
| 2014 | 0.8860 | 0.0410 | 0.8170 | 0.990 | 2020 | 0.9000 | 0.0400 | 0.8400 | 1.0000 |
| 2015 | 0.8930 | 0.0420 | 0.8350 | 1.000 | Pooled | 0.8900 | 0.0450 | 0.7900 | 1.0000 |
| | | | | | West Region | | | | |
| 2010 | 0.8670 | 0.0520 | 0.7810 | 0.941 | 2016 | 0.927 | 0.047 | 0.8770 | 1.0000 |
| 2011 | 0.8620 | 0.0600 | 0.7930 | 1.000 | 2017 | 0.927 | 0.043 | 0.8680 | 0.9970 |
| 2012 | 0.8720 | 0.0550 | 0.8160 | 0.990 | 2018 | 0.9260 | 0.0440 | 0.8630 | 1.0000 |
| 2013 | 0.8900 | 0.0490 | 0.8250 | 1.000 | 2019 | 0.9190 | 0.0490 | 0.8590 | 1.0000 |
| 2014 | 0.9070 | 0.0390 | 0.8510 | 0.990 | 2020 | 0.9400 | 0.0500 | 0.8670 | 1.0000 |
| 2015 | 0.9100 | 0.0400 | 0.8550 | 0.994 | Pooled | 0.9040 | 0.0530 | 0.7810 | 1.0000 |

Year: time of economic efficiency measures. Pooled: overall mean of economic efficiency measures. std.dev: standard deviation of economic efficiency measures. Minimum: minimum economic efficiency measures over time. Maximum: maximum economic efficiency measures over time.

and solvency risks are offset to some extent by the COVID-19 crisis. On the other hand, with the fixed effect regression model that controls for unobserved heterogeneity, the coefficients of interaction terms, COVID-19 × liquidity and COVID-19 × solvency, are positive and significant at the 5 percent significance level. This implies that the sensitivity of economic efficiency measures estimates to the COVID-19 is more pronounced in U.S. commercial and domestic banks with efficient liquidity and solvency. Furthermore, our results provide evidence that the positive and significant estimates of the interaction terms, COVID-19 × liquidity and COVID-19

**Table 7.** Regional economic efficiency measures under Scale assumption

| Year | Mean | Std.dev | Minimum | Maximum | Year | Mean | Std.dev | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Midwest Region | | | | |
| 2010 | 0.9440 | 0.0310 | 0.8650 | 1.0000 | 2016.0000 | 0.9130 | 0.0370 | 0.8170 | 0.9990 |
| 2011 | 0.9400 | 0.0320 | 0.8490 | 1.0000 | 2017.0000 | 0.9130 | 0.0400 | 0.8110 | 0.9990 |
| 2012 | 0.9320 | 0.0320 | 0.8360 | 1.0000 | 2018.0000 | 0.9180 | 0.0370 | 0.8000 | 1.0000 |
| 2013 | 0.9260 | 0.0340 | 0.8260 | 1.0000 | 2019.0000 | 0.9190 | 0.0360 | 0.8040 | 0.9980 |
| 2014 | 0.9190 | 0.0340 | 0.8280 | 1.0000 | 2020.0000 | 0.9160 | 0.0380 | 0.7740 | 1.0000 |
| 2015 | 0.9140 | 0.0350 | 0.8180 | 0.9990 | Pooled | 0.9230 | 0.0370 | 0.7740 | 1.0000 |
| | | | | | Northeast Region | | | | |
| 2010 | 0.9240 | 0.0320 | 0.8640 | 1.0000 | 2016.0000 | 0.8930 | 0.0360 | 0.8100 | 1.0000 |
| 2011 | 0.9180 | 0.0280 | 0.8570 | 0.9730 | 2017.0000 | 0.8870 | 0.0320 | 0.8030 | 0.9550 |
| 2012 | 0.9130 | 0.0290 | 0.8400 | 0.9750 | 2018.0000 | 0.8900 | 0.0320 | 0.8290 | 0.9530 |
| 2013 | 0.9040 | 0.0310 | 0.8340 | 0.9770 | 2019.0000 | 0.9000 | 0.0330 | 0.8380 | 0.9770 |
| 2014 | 0.8990 | 0.0340 | 0.8270 | 0.9860 | 2020.0000 | 0.8950 | 0.0320 | 0.8260 | 0.9770 |
| 2015 | 0.8990 | 0.0390 | 0.8240 | 0.9950 | Pooled | 0.9020 | 0.0340 | 0.8030 | 1.0000 |
| | | | | | South Region | | | | |
| 2010 | 0.931 | 0.0310 | 0.8630 | 1.0000 | 2016.0000 | 0.8910 | 0.0340 | 0.8100 | 0.9830 |
| 2011 | 0.9280 | 0.0340 | 0.8420 | 1.0000 | 2017.0000 | 0.8910 | 0.0400 | 0.8040 | 1.0000 |
| 2012 | 0.9200 | 0.0320 | 0.8320 | 0.9990 | 2018.0000 | 0.8910 | 0.0370 | 0.8110 | 1.0000 |
| 2013 | 0.9110 | 0.0340 | 0.8180 | 0.9900 | 2019.0000 | 0.8940 | 0.0350 | 0.7980 | 0.9900 |
| 2014 | 0.9010 | 0.0350 | 0.8180 | 0.9760 | 2020.0000 | 0.8910 | 0.0380 | 0.7830 | 0.9980 |
| 2015 | 0.8940 | 0.0350 | 0.8160 | 0.9810 | Pooled | 0.9040 | 0.0380 | 0.7830 | 1.0000 |
| | | | | | West Region | | | | |
| 2010 | 0.9210 | 0.0300 | 0.8890 | 0.9820 | 2016 | 0.8620 | 0.0490 | 0.7950 | 0.9510 |
| 2011 | 0.9220 | 0.0400 | 0.8810 | 1.0000 | 2017 | 0.8600 | 0.0430 | 0.8010 | 0.9340 |
| 2012 | 0.9110 | 0.0440 | 0.8550 | 0.9970 | 2018 | 0.8610 | 0.0390 | 0.8130 | 0.9300 |
| 2013 | 0.8980 | 0.0470 | 0.8390 | 1.0000 | 2019 | 0.8730 | 0.0390 | 0.8170 | 0.9470 |
| 2014 | 0.8830 | 0.0480 | 0.8170 | 0.9740 | 2020.0000 | 0.8610 | 0.0420 | 0.7990 | 0.9360 |
| 2015 | 0.8750 | 0.0470 | 0.8080 | 0.9640 | Pooled | 0.8840 | 0.0470 | 0.7950 | 1.0000 |

Year: time of economic efficiency measures. Pooled: overall mean of economic efficiency measures. std.dev: standard deviation of economic efficiency measures. Minimum: minimum economic efficiency measures over time. Maximum: maximum economic efficiency measures over time.

× solvency, on U.S. commercial and domestic banks' economic efficiency measures is an indication of the critical role of both liquidity and solvency sharing in the banking sector towards financial consumer protection, especially during the pandemic.

Additionally, the results of Table 8 highlight a key difference between both liquidity and solvency risks. Depending on the regional classification, U.S. commercial and domestic banks that are heavily exposed to the COVID-19 crisis are more susceptible to losses due to the likelihood of defaults. Furthermore, based on the results of Table 8 we can state that the Federal Reserve and U.S. Treasury Department helped alleviate the sharp tightening of financial conditions at the onset of the crisis. Depending on the region, COVID-19 has either a positive (Northeast) or negative (Midwest, South, and West) effect. The significant negative effect of COVID-19 might be due to the regulatory intervention in response to COVID-19 (example, low interest rate) by the Federal Reserve.

## 6 Conclusions and policy implications

The widely spread of COVID-19 represents an unpresented shock on the U.S. economy. Thus, U.S. commercial and domestic banks are expected to play an important role in absorbing the shock by supplying vital credit to the corporate sector and households. To facilitate this, the Federal Reserve Board and the U.S. Treasury Department enacted a wide range of policy measures to provide greater liquidity and support the flow of credit. Therefore, the evaluation of COVID-19 affecting the economic efficiency measures of U.S. commercial and domestic banks is an important concept that addresses the issues of maintaining confidence and stability in the banking sector.

This paper applies a two-step approach analysis, economic efficiency estimation and regression technique, Tobit and panel fixed effect, to evaluate the impact of COVID-19 on economic efficiency measures. In the first step, economic efficiency measures of U.S. commercial and domestic banks are estimated using the nonparametric Data Envelopment Analysis. In the second step, Tobit and fixed effect regression models are used to evaluate the impact of COVID-19, in addition to regulatory factors, liquidity and solvency, and bank internal factor, bank's size, on economic efficiency measures.

**Table 8.** Impact of COVID-19 on economic efficiency measures by U.S Region.

| Parameter | Tobit | | Fixed Effect | |
|---|---|---|---|---|
| | Estimate | Standard Error | Estimate | Standard Error |
| **Midwest Region** | | | | |
| Intercept | 1.04126*** | 0.05757 | 0.95480*** | 0.02441 |
| *COVID – 19* | -0.08649* | 0.05678 | -0.08649* | 0.05707 |
| *Liquidity* | 0.00552 | 0.00356 | -0.00119 | 0.00142 |
| *Liquidity × COVID – 19* | -0.00672* | 0.00383 | -0.00672* | 0.00385 |
| *solvency* | 0.01855 | 0.02212 | -0.00170 | 0.00557 |
| *solvency × COVID – 19* | -0.02025* | 0.02280 | -0.02025* | 0.02292 |
| Bank's size | -0.00303*** | 0.00115 | -0.00303*** | 0.00116 |
| $\sigma$ | 0.03613*** | 0.00098 | | |
| Performance | | | | |
| LogLikelihood | 1299.00 | | 1265.35 | |
| AIC | -2582.00 | | -2528.70 | |
| BIC | -2545.00 | | -2524.20 | |
| **Northeast Region** | | | | |
| Intercept | 0.90500*** | 0.07690 | 1.07990*** | 0.03463 |
| *COVID – 19* | 0.17487** | 0.07862 | 0.17490** | 0.07947 |
| *Liquidity* | -0.00380 | 0.00476 | 0.00329* | 0.00204 |
| *Liquidity × COVID – 19* | 0.00709 | 0.00517 | 0.00709 | 0.00523 |
| *solvency* | -0.05786* | 0.03288 | -0.00272* | 0.00952 |
| *solvency × COVID – 19* | 0.05514 | 0.03420 | 0.05514 | 0.03456 |
| Bank's size | -0.01061*** | 0.00145 | -0.01061*** | 0.00146 |
| $\sigma$ | 0.03113*** | 0.00121 | | |
| Performance | | | | |
| LogLikelihood | 674.639 | | 643.450 | |
| AIC | -1333.000 | | -1284.900 | |
| BIC | -1303.000 | | -1281.100 | |
| **South Region** | | | | |
| Intercept | 1.07730*** | 0.07492 | 0.92050*** | 0.02687 |
| *COVID – 19* | -0.15681** | 0.07504 | -0.15680** | 0.07553 |
| *Liquidity* | 0.00754 | 0.00505 | 0.00356** | 0.00157 |
| *Liquidity × COVID – 19* | -0.00398 | 0.00529 | -0.00398 | 0.00532 |
| *solvency* | 0.05768** | 0.02333 | -0.00930* | 0.00520 |
| *solvency × COVID – 19* | -0.06698*** | 0.02390 | -0.06698*** | 0.02406 |
| Bank's size | -0.00052 | 0.00131 | -0.00052 | 0.00132 |
| $\sigma$ | 0.03703*** | 0.00113 | | |
| Performance | | | | |
| LogLikelihood | 1010.00 | | 977.15 | |
| AIC | -2004.00 | | -1952.30 | |
| BIC | -1969.00 | | -1948.00 | |
| **West Region** | | | | |
| Intercept | 1.09275*** | 0.24371 | 0.85390*** | 0.08719 |
| *COVID – 19* | -0.23888* | 0.24589 | -0.23890* | 0.25270 |
| *Liquidity* | 0.00196 | 0.01010 | 0.00531 | 0.00468 |
| *Liquidity × COVID – 19* | 0.00335 | 0.01106 | 0.00334 | 0.01136 |
| *solvency* | 0.07024 | 0.08827 | -0.05851** | 0.02022 |
| *solvency × COVID – 19* | -0.12875* | 0.09017 | -0.12880* | 0.09266 |
| Bank's size | -0.00379 | 0.00266 | -0.00379 | 0.00274 |
| $\sigma$ | 0.04402*** | 0.00271 | | |
| Performance | | | | |
| LogLikelihood | 224.956 | | 199.200 | |
| AIC | -433.911 | | -396.400 | |
| BIC | -410.849 | | -393.500 | |

The AIC and BIC can be used to compare nested and non-nested models. $\sigma$ is equivalent to the square root of the residual variance in Tobit regression. Standard Error values are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

Using a sample consisted of a panel dataset of 16,830 observations spanning from December 2010 through December 2020, the economic efficiency measures are estimated via the DEA model under the constant returns-to-scale, variable returns-to-scale, and scale assumptions while accounting for the yearly variability. In accounting for the yearly variability, we allow the economic efficiency measures to differ through the technological change. The empirical estimates of the economic efficiency measures and different factors influencing the cost inefficiency terms present distinctive conclusions.

First, in looking into the economic efficiency measures from 2010 to 2020, the results of Table 3 suggest that the U.S. domestic and commercial banks have been affected by the COVID-19 and economic shocks of the period. This is reflected in the decreased of economic efficiency measures in 2020. The effect of COVID-19 in the banking sector can be viewed in two dimensions. First, high transmissions and mortality rates of COVID-19 reduce the supply of exchanges of U.S. Dollars, which, in turn, hinders production in the banking sector (Zheng and Zhang, 2021). And second, social distancing policies and lockdown measures used to reduce the transmission rate and curb the spread of COVID-19, also result in a sharp and immediate decline of the profitability of banks (Zheng and Zhang, 2021). That is, when banks' customers lose their income due to the mass layoffs, they tend to cut back on spending or reduce their social consumption and thus delay their investments owing to heightened uncertainty associated with the COVID-19.

Additionally, the decreased of economic efficiency measures is observed by the negative effect of the

COVID-19 on the economic efficiency measures. Furthermore, we observe that both liquidity and solvency risks are positive and significant at a 1 percent significance level across both Tobit and fixed effect regression models. However, during the COVID-19, the parameter estimates of both liquidity and solvency risks are negatively related to the economic efficiency measures of U.S. commercial and domestic banks, and thus, indicating that a downturn in the bank's efficiency. Thus, we observe that U.S. commercial and domestic banks' liquidity negatively collapses due to contagion. In addition, the capital adequacy is significantly and negatively related to the economic efficiency suggesting that high capital requirements decrease the economic efficiency of U.S. commercial and domestic banks during the COVID-19.

Second, bank's size is negatively related to the economic efficiency measures of U.S. commercial and domestic banks and thus suggesting that the amount of total assets of banks does matter in the improvement of economic efficiency measures. And finally, while accounting for the regional classifications, Midwest, Northeast, South, and West, the established negative effect of COVID-19 on bank economic efficiency measures is consistent across Midwest, South, and West. In addition, it reveals that this relationship could be either symmetric or asymmetric in Midwest, South, and West regions. Thus, we conclude that the interaction terms, between COVID-19 and liquidity risk and between COVID-19 and solvency risk, leads to more accurate results which enhances a better insightful of a banking policy. The policy implication of our paper demonstrates that the policies of liquidity and solvency factors are significant procedures to improve economic performance and particularly during the COVID-19.

Our findings follow the conclusion of Sakouvogui and Shaik (2020) and thus suggest that capital requirements strengths financial stability by providing a larger capital buffer. This study has room for more research that will provide even more detailed view about the evaluation of exogenous variables on the cost efficiency measures during the COVID-19. Different sets of variables could be used to compare results between models. More importantly, compared to the current framework, the results of the efficiency measures could vary regarding the first and second moments of the economic efficiency measures depending on the country. It could be great to further incorporate the stimulus as a dummy and study its implication on the economic efficiency measures of precisely developing countries.

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