U.S. agricultural banks' efficiency under Covid-19 Pandemic conditions: A two-stage DEA analysis

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1. Introduction

Towards the end of 2019, the coronavirus (Covid-19) pandemic began to strike the global economy with the biggest shock since the Great Depression. Countries closed their borders and trade transactions were disrupted as factories shut down. The resulting reduction in economic activities caused by the lockdowns and a slump in consumer spending threatened the global economy with another recession. In the United States, the Bureau of Economic Analysis estimates that real gross domestic product (GDP) decreased by 5.0 percent and 32.9 percent in the first and second quarters of 2020, respectively. Expected economic recessionary impacts have been mitigated by prompt and effective government interventions in financial markets. The government's actions include easing regulatory requirements and loan payment deferments, among others. These concessions averted a deeper catastrophe that would have befallen financial institutions during the pandemic. However, the systematic vulnerability is still very likely to increase in the banking sector, as the banking sector's overall income has substantially decreased in absolute terms, which, in turn, raises the concerns of the pandemic's impact on banking operating efficiency.

A banks' performance is usually gleaned from accounting ratios, such as return on assets and leverage ratio. Although the ratios provide valuable information about a bank's financial performance, they do have some limitations. First, the ratios aggregate many dimensions of operating performance. A bank may be indicated as performing well in one metric, even if it performs very poorly in some other aspects. Second, financial ratios fail to consider the importance of management or investment decisions (Sherman & Gold, 1985). Banking efficiency is always of interest, as it can not only provide valuable information for government policies but also can be used to improve managerial performance and control risk. It is widely recognized that banks with low-efficiency levels have higher probabilities to fail than those with higher efficiency levels (Berger & Humphrey, 1997).

Among the many studies evaluating the efficiency of banks and other types of financial institutions, only a few addressed the efficiency of agricultural banks. This study is motivated by the issue and tries to provide the initial exploration of the impacts of Covid-19 on U.S. agricultural banking efficiency.

The present study examines the efficiency of U.S. agricultural banks using nonparametric Data Envelopment Analysis (DEA) over the period starting from the first quarter of 2017 until the second quarter of 2020. Compared to other parametric methodologies such as Stochastic Frontier Analysis (SFA), DEA does not require an explicit specification of the form of the underlying production relationship. It also allows multiple inputs and outputs, making it more attractive. Unlike many other studies, the current study employs three different approaches in defining agricultural banks' inputs and outputs to evaluate the efficiency thoroughly: the intermediation approach, operating approach, and value-added approach. To investigate the impacts of the pandemic, a second-stage multivariate regression is used, after controlling bank-specific characteristics and macroeconomic conditions.

The rest of the paper is structured as follows: Section 2 reviews related studies using the DEA method in banking and efficiency studies in agricultural banks. Section 3 provides the conceptual framework for measuring efficiency using the DEA methodology. Section 4 presents the data and the basic statistics of variables. Section 5 provides the results of the efficiencies of U.S. agricultural banks obtained by DEA as well as the second-stage multivariate regression results. The final section, section 6, provides concluding remarks.

2. Literature Review

DEA applications in banking

Data envelopment analysis is an efficient frontier method designed to determine the best performing decision-making units (DMUs) by comparing non-frontier DMUs with their distance to the best practice frontier. This analytical method was first introduced by Charnes, Cooper, and Rhodes (1978). Sherman and Gold (1985) pioneered the application of the DEA approach to the banking industry. They claim that DEA results could provide a beneficial and meaningful contribution to literature. Since then, several subsequent DEA applications were reported in empirical studies.

Some studies focus on the impact of regulatory policies on banking efficiencies. Although one of the main goals of deregulation is increasing efficiencies, different markets may have different results. Elyasiani and Mehdian (1990) employ DEA to derive the efficiency and the rate of technological change for about 200 largest U.S. commercial banks. Their results indicate the banks in the sample became less efficient from 1980 to 1985, with significant progress in the rate of technological change. Berg, Forsund, and Jansen (1992 a) use DEA to study productivity growth during the period of deregulation in the Norwegian banking industry. They conclude that Norwegian banks increased their efficiency and productivity after the deregulation. Similar results were obtained by Zaim (1995) and Isik and Hassan (2003) in their analyses of Turkish institutions in the 1980s. Sturm and Williams (2004) also conclude that banking efficiency increased after deregulation when they studied the Australian banking industry post-deregulation period in 1988 to 2001.

Ozkan-Gunay et al. (2013) investigate how regulatory policies impact the efficiency of commercial banks for different sizes using Turkish banking data from 2002 to 2010. Their results indicate that regulatory policies have a positive impact on banks' efficiency, with large-size and medium-size banks producing better results than medium-large and small banks. They also find that efficiencies are much lower, when adding nonperforming loans into the DEA model. However, banking efficiencies were relatively unchanged by the deregulation in the U.S. market (Elyasiani & Mehdian, 1995). Although small banks were more efficient during the pre-deregulation period, their efficiencies were similar in the post-deregulation period. The results of Grifell-Tatje and Lovell (1996) also indicate that deregulation has little effect on the efficiency of Spanish banks.

The impacts of the financial crises on banking efficiencies also receive significant study. Sufian (2009) investigates the efficiencies of Malaysian banks around the 1997 Asian financial crisis. The results show a high degree of efficiency decline, especially a year after the crisis. Similar results were obtained by Fukuyama and Matousek (2011) for Turkish banks after both the 1994 currency crisis and the 2001financial crisis. Gulati and Kumar (2016) studied Indian banks' performance around the 2008 global financial crisis. Their results indicate no long-adverse effect of the crisis on Indian banks' profit efficiency.

Another topic that attracts attention in financial institutions is how to improve managerial performance. There are ample studies performing ex-post analyses in identifying the most significant determinants of banking efficiencies. Efficiency studies of financial institutions can be a tool by owners and managers to improve firms' performance. The closer a firm is to the efficient frontier, or the farther away it is from the "worst practices" benchmark, the stronger the firm is when facing risks.

Pancurova and Lyocsa (2013) investigate bank efficiencies and their determinants for eleven Central and Eastern European Countries in the 2005 – 2008 period. Their results indicate 1) bank size and financial capitalization have positive impacts on cost and revenue efficiency; 2) compared to domestic banks, foreign banks are more cost-efficient but less revenue efficient; and 3) cost efficiency is negatively affected by the loans-to-assets ratio, but revenue is positively affected by the ratio. Said et al. (2013) analyzed selected Islamic and conventional commercial banks in Malaysia. The results indicate that capitalization and bank size positively impact efficiency, but loan quality is negatively associated with efficiency. Luo (2003) uses a sample of 245 U.S. large banks to show that the geographical location of banks is not a significant factor in explaining bank efficiencies. Wang et al. (2014) point out that nonperforming loans can generally explain banks' efficiency in China's banking system, when evaluating 16 major Chinese commercial banks in the third round of the Chinese banking reform period (2003 – 2011).

Efficiency studies in Agricultural banking

Efficiency-related studies for agricultural banks also receives significant attention since operations of agricultural banks are crucial to the success of the U.S. agricultural economy. Among several agricultural banking studies, Neff et al. (1994) applied the SFA method to measure the efficiency of the US. agricultural banks. Their study finds that the estimated cost and profit efficiencies are very different, where profit inefficiencies are found to be much higher than cost inefficiencies.

Dias and Helmers (2001) study how post-deregulation, structural changes have impacted agricultural banks and identify sources of productivity growth in both agricultural and nonagricultural banks, by employing a DEA approach.[1] They find that for both types of banks, larger banks gain productivity mainly from technical changes or innovation, while smaller banks increase efficiency through catching up with frontier banks to improve their competitive strength. Li, Brewer and Escalante (2018) use an Input Distance Stochastic Frontier function to estimate the technical efficiency and allocative efficiency of agricultural and non-agricultural banks. Their results indicate that surviving banks were more technically efficient than failed banks. Additionally, banks that tend to employ cheaper inputs are more resilient and have more economic endurance to withstand the financial crisis. Choi, Stefanou, and Stokes (2007) apply both SFA and DEA by using a balanced panel data set of 519 agricultural banks from 1996 to 2005. Their results suggest that (a) bank profitability is positively related to cost efficiencies, (b) younger agricultural banks are less efficient than older ones, (c) bank efficiencies are negatively related to regulations, (d) larger agricultural banks are less efficient than smaller

[1] Deregulation occurred with the passing of the Depository Institutions Deregulation and Monetary Control Act of 1980.

ones, (e) DEA efficiency scores can be explained better by bank-specific attributes than SFA, and (f) inconsistency is not a serious problem in two-step approaches.

3. Methodology

3.1 Data Envelopment Analysis

Due to its advantages of imposing less structure on the frontier in measuring efficiencies, the nonparametric Data Envelope Analysis (DEA) receives considerable attention in academics, notwithstanding the drawback of assuming no random error. In DEA, a bank is called a DMU (Decision Making Unit), which can convert K inputs of x into M outputs of y. In principle, larger output amounts with smaller input volume are preferable.

The DEA model is first proposed by Charnes, Cooper and Rhodes (1978) and was initially known as the CCR model. In the CCR model, the production possibility set is based on the constant returns-to-scale assumption. In the model, the objective of each DMU is to minimize its inputs while keeping its output levels fixed.[2] The technical efficiency of each DMU can be reached as a solution to the following optimization program:

$$\begin{aligned} & \min \theta \\ \text{St:} \quad & \textstyle\sum_j \lambda_j X_{ij} \leq \theta X_{i0} \\ & \textstyle\sum_j \lambda_j Y_{rj} \geq Y_{r0} \\ & \lambda_j \geq 0 \end{aligned}$$

where X_{ij} and Y_{rj} are the amounts of inputs consumed and output generated, respectively, by the *j*th bank. However, the assumption of constant returns to scale in the above model is only appropriate when all DMUs are operating at an optimal scale.

To relax the assumption of constant returns to scale, Banker, Charnes and Cooper (1984) modified the CCR model by allowing variable returns to scale. This model was subsequently labelled and known as the BCC model. The input-oriented BCC model evaluates a DMU's efficiency by solving the following linear program:

$$\begin{aligned} & \min \eta \\ \text{St:} \quad & \textstyle\sum_j \lambda_j X_{ij} \leq \eta X_{i0} \\ & \textstyle\sum_j \lambda_j Y_{rj} \geq Y_{r0} \\ & \textstyle\sum \lambda_j = 1 \\ & \lambda_j \geq 0 \end{aligned}$$

[2] It should be noted that both input orientation and output orientation are allowed in DEA, for simplicity, we only show the input orientation.

The essential difference between CCR model and BCC model is that the BCC model adds the new constraint $\sum \lambda_j = 1$. The constraint ensures that an inefficient DMU is more comparable to banks with similar sizes. As a result, BBC efficiency scores are larger or equal to CCR efficiency scores. The comparison between CCR model and BCC model can be illustrated by a simple example of 4 firms, A B, C and D, each with one input and one output, in figure 1.

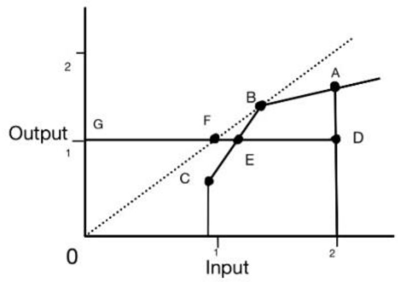

Figure 1. Comparison of CCR model and BCC model

The dotted line passing through 0 and B represents the efficient frontier of the CCR model. The BBC model consists of the bold lines connecting A, B and C. The production possibility set is the area under the frontier. In this example, B is both BCC- and CCR- efficient. But A and C are only BCC efficient. For D, the BCC-efficiency is calculated by GE/GD, while CCR-efficiency is evaluated by GF/GD, with a smaller value.

The efficiency obtained from the CCR model, also called technical efficiency (TE), measures a DMU's ability to transform multiple inputs into multiple outputs. This is a comparative measure of how far the DMU is from the production frontier. TE can be decomposed into two components: pure technical efficiency (PTE) and scale efficiency (SE). PTE, which is also the BCC-efficiency, measures how effectively a manager uses and organizes available inputs when given a fixed output level, during the operating process. On the other hand, SE (i.e., SE=TE/PTE) reflects the manager's ability to choose the agricultural bank's scale of operations to attain the expected output level. An agricultural bank is considered scale efficient if operating at constant returns-to-scale (CRS).

3.2 Determinants of agricultural banks' efficiency

In determining the effects of Covid-19, as well as other macro and bank-specific factors on banking efficiency, the efficiency scores obtained from the first stage are regressed with variables potentially related. Various techniques are used by different scholars in the second stage. Banker and Natarajan (2008) suggest that ordinary least squared (OLS), maximum likelihood, and the Tobit regression may be appropriate. McDonald (2009) prefers OLS over the Tobit model by showing that the efficiency scores are fractional data but not generated by a censoring process. In this study, we will use OLS as suggested by McDonald (2009).

In specifying the determinants of a bank's efficiency, both its specific performance-related and the pervading environmental factors need to be considered. The model in this analysis is specified by the following equation:

$$Eff = a + b1\ Covid + b2\ Macros + \ b3B + e$$

Covid is a dummy variable that is 1 if the data is from the period during the Covid-19 pandemic and 0 otherwise; *Macros* is a vector of macroeconomic variables including GDP, unemployment rate, and state housing price index. When economic conditions deteriorate, borrowers' financial conditions are very likely to underperform. We expect a positive impact of GDP and a negative impact from the unemployment rate. The impacts of an increase in the housing price index remains unclear, since it will increase borrowers' overall cost, but will also ease borrowers' access to credit (borrowers can use their homes as collateral to boost their loan applications' probability of getting approved).

B is a vector of bank-specific characteristics for each bank. Bank specific attributes may have potential impacts on banks' efficiencies. We first include a set of standard variables such as banks' capital strength, loan quality, management quality, profitability, and liquidity, as suggested by previous literatures studying bank performance (e.g., Bremus & Ludolph, 2021). We measure capital strength as total equity divided by total assets, loan quality as the loan loss provision over total loans, management quality by noninterest expense to total income, profitability by return on equity and net interest margin, and liquidity by loans to assets ratio. We also control bank for size, as suggested by Das and Ghosh (2006). The natural logarithm of total assets is used as a proxy of bank size to capture economies of scale. A large bank tends to have better management skills, and likely to have a higher efficiency level.

Besides the traditional bank-specific variables, we include several more bank attributes that may explain efficiency levels. We first consider the loan portfolio structures of each agricultural bank. Loan portfolio structure measures the extent of diversification of the bank's risky asset (loans) among various loan types, as suggested by Li et al. (2013). The index is calculated as the sum of the squares of the shares of the loan mix to various sectors of the economy, including real estate loans, agricultural loans, individual loans, and commercial & industrial loans. This captures the extent of diversification of banks' risky asset (loans) among different loan types. The nonperforming loans ratio (NPL) is also controlled for in the second stage. The banks' noninterest activities ratio is controlled as well. Banks' interest income is often earned from banks' traditional core activities like lending loans and taking deposits, while noninterest income often come from resources unrelated to the collection of interest payment. The noninterest activities ratio is measured as noninterest income to total income, which allows us a closer look at a bank's income structure. Additionally, we include the ratio of dividend to net income. Although the ratio may not directly reflect a bank's financial health, it indicates how the bank values its investment in future growth.

3.3 Specification of bank inputs and outputs

The selection of inputs and outputs for DEA models has been widely discussed and no simple consensus has been reached. There are two main approaches in the current literature: the intermediation approach and the production approach. The operating approach and the value-added approach are more recent approaches.

The production approach defines financial institutions as providers of services for account holders. Financial institutions process loan applications and perform transactions. According to this approach, the number of different types of transactions, accounts or documents is the best measure for output. In addition, the production approach only considers physical inputs, such as labor, capital, and their costs (Berger & Humphrey, 1997).

Under the intermediation approach, banks are seen as financial intermediaries between borrowers and depositors. Banks purchase funds and collect deposits, and then, as an intermediary, they re-channel the money into their other transactions as loans and other assets. Berger and Humphrey (1997) point out that the production approach is better for evaluating branches of a bank, while the intermediation approach is more appropriate for evaluating a whole bank's efficiency.

The operating approach, also known as the income approach, views banks as business units whose main objective is producing income from expenses incurred. Thus, the inputs are interest and non-interest expenses, while the outputs are interest and non-interest incomes. Finally, under the value-added approach, also known as the revenue approach, items that can add value to a bank, generally deposits and loans, are viewed as outputs.

There is reasonable agreement that labor, capital and expenses are important inputs. Also it is common to assume that loans and other major assets are outputs. However, there has been much debate on whether to treat deposits as inputs or outputs since deposits have characteristics of both. As an input, deposits can be provided to institutions as funds. Deposits can also be an output since institutions generate a large amount of revenue from deposits.

This study focuses mainly on three approaches: intermediation approach, operating approach, and value-added approach. Because the present study analyzes data from banks as a whole, not individual branches, we do not analyze efficiency using the production approach.

Following Sufian (2009), under the intermediation approach, we assume labor, capital and deposits as inputs, and total loans and investments as output. For the operating approach, we consider labor, interest expense and noninterest expenses as inputs, and interest income and noninterest income as outputs. Under the value-added approach, we use three inputs of labor, capital, and interest expenses, and three outputs of loans, investments, and deposits. The input and output variables included in our models are summarized in table 1.

Table 1. Inputs and Outputs For DEA

Intermediation Approach		Operating Approach		Value-added Approach	
Inputs	Outputs	Inputs	Outputs	Inputs	Outputs
Labor	Total Loans	Labor	Interest Income	Labor	Total Loans
Capital	Investments	Interest Expense	Noninterest Income	Capital	Investments
Total Deposits		Noninterest Expense		Interest Expense	Total Deposits

4. Data

For this analysis, a panel dataset is compiled for all agricultural banks operating in the U.S. banking sector from the first quarter of 2017 to the second quarter of 2020. According to the definition of the Federal Deposit Insurance Corporation (FDIC), a bank is defined as an "agricultural bank" if at least 25 percent of its total loan has been extended to the agricultural sector. The final dataset contains 497 agricultural banks. The bank-level data are obtained from the Call Reports Data from the Federal Financial Institutions Examination Council (FFIEC) Central Data Repository (CDR) Public Data Distribution (PDD) website.

Macroeconomic data like state GDP was obtained from the Bureau of Economic Analysis (BEA). Unemployment rates for each state are sourced from the U.S. Bureau of Labor Statistics

(BLS). Housing Price Index (HPI) data are retrieved from the Federal Housing Financial Agency (FHFA). The descriptive statistics of input and output variables are summarized in table 2. Table 3 summarizes the second stage variables description and summary statistics.

Table 2. Descriptive statistics for inputs and outputs

			2017	2018	2019	2020
Inputs	Labor	mean	27.412	27.81	28.465	28.767
		sd	37.251	38.075	39.277	39.944
	Total Deposits	mean	115816.224	121423.454	126196.305	135217.821
		sd	140105.554	161113.444	158352.642	168668.461
	Capital	mean	17167.581	17845.809	19562.927	20623.056
		sd	28952.055	31287.535	33671.065	35420.635
	Interest Expense	mean	477.652	660.13	949.054	514.42
		sd	1567.753	2282.215	2921.204	1292.033
	Noninterest Expense	mean	2139.859	2242.107	2372.741	1467.156
		sd	3913.746	4155.94	4326.238	2501.96
Outputs	Total Loans	mean	98791.784	103905.188	108435.695	113021.838
		sd	183226.161	195964.548	201725.632	208937.831
	Investment	mean	37608.496	37832.819	39784.444	45595.619
		sd	44558.692	44304.066	46306.455	53480.405
	Interest Income	mean	3667.189	4058.363	4488.779	2655.758
		sd	8618.738	9714.564	10462.767	5364.636
	Noninterest Income	mean	537.111	552.379	590.264	369.428
		sd	2397.833	2490.903	2575.236	1502.847

Table 3. Second stage variables description and summary statistics

Bank-specific variables	*Descriptions*	Mean	SD
HERLOAN	$AGRI^2 + REAL^2 + COMM^2 + INDI^2$	0.394	0.067
NPL	Nonperforming loans	0.014	0.025
ROE	Net income divided by equity	0.056	0.065
ETA	Equity divided by assets	0.126	0.037
LTA	Total loans dived by assets	0.629	0.169
LLPTL	Loan loss provision divided by total loans	0.002	0.005
NITI	Noninterest income divided by total income	0.089	0.068
NETI	Noninterest expense divided by total income	0.546	0.134
DTI	Dividend divided by net income	0.617	1.024
ASST	Total assets	152647.5	227317.7
NIM	Net interest margin	0.020	0.010
Macro Variables			
GDP	GDP	300253.6	395846.8
UEM	Unemployment rate	0.04389	0.023746
HPI	Price index of residential home values	337.8766	60.84282

5. Results and discussion

In this section, we discuss how the technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) change among agricultural banks, by solving the DEA method. In the first subsection, the differences among the three approaches are compared. In the second subsection, we investigate if the efficiency scores are affected by the Covid-19 outbreak, some bank-specific characteristics, as well as other macroeconomic variables.

5.1 Efficiency of Agricultural banking sector

Table 4 summarizes the means of the TE scores for U.S. agricultural banks under the three different approaches, from the first quarter of 2017 to the second quarter of 2020. Different estimated TE scores are produced by different sets of inputs and outputs. Based on the DEA results, we can see that U.S. agricultural banks are technically inefficient although the highest mean efficiency scores are obtained under the intermediation approach. The overall average efficiency score for the intermediation approach is about 74.76 %, with a quarterly average ranging from 73.5% to 75.6%. The estimated average efficiency for the operating approach is lowest, at about 45.42%, while estimated efficiency for the value-added approach is between them, at about 66.73%.

Table 4. Technical efficiency (TE) score by quarter

	Intermediation approach			Operating approach			Value-added approach		
year	Mean	SD	Efficient banks	Mean	SD	Efficient banks	Mean	SD	Efficient banks
2017q1	0.755	0.0789	2	0.44	0.134	1	0.764	0.127	12
2017q2	0.752	0.0766	1	0.464	0.136	2	0.688	0.116	2
2017q3	0.751	0.0775	0	0.499	0.136	1	0.656	0.114	0
2017q4	0.751	0.079	1	0.548	0.132	3	0.65	0.115	1
2018q1	0.756	0.0791	2	0.41	0.118	1	0.744	0.124	11
2018q2	0.753	0.0779	2	0.436	0.122	2	0.678	0.116	2
2018q3	0.753	0.0789	1	0.477	0.126	1	0.648	0.115	2
2018q4	0.745	0.0762	0	0.528	0.129	1	0.632	0.114	0
2019q1	0.745	0.077	2	0.382	0.122	2	0.692	0.113	6
2019q2	0.74	0.0761	1	0.415	0.123	0	0.632	0.11	2
2019q3	0.735	0.0751	2	0.464	0.131	1	0.606	0.109	1
2019q4	0.736	0.0754	3	0.515	0.133	4	0.604	0.113	4
2020q1	0.743	0.0774	2	0.367	0.119	2	0.684	0.114	6
2020q2	0.751	0.077	2	0.415	0.125	1	0.665	0.113	3
Overall	0.748	0.078		0.454	0.138		0.667	0.124	

The number of efficient banks (TE = 1) during the sample period ranged from 0 to 3 under the intermediation approach and 0 to 4 under the operating approach. On the other hand, the number of efficient banks is highest under the value-added approach, ranging from 0 in the third quarter of 2017 and the fourth quarter of 2018 to 12 in the first quarter of 2017. Overall, there is no apparent change in both efficiency scores and the number of efficient banks after the outbreak of Covid-19. In addition, no evidence is shown on the dispersion of technical efficiency scores, as measured by its standard deviation.

Table 5. Pure technical efficiency (PTE) score by quarter

year	Intermediation approach			Operating approach			Value-added approach		
	Mean	SD	Efficient banks	Mean	SD	Efficient banks	Mean	SD	Efficient banks
2017q1	0.778	0.0841	7	0.505	0.149	2	0.797	0.129	32
2017q2	0.775	0.0816	1	0.551	0.152	4	0.723	0.119	5
2017q3	0.774	0.0813	3	0.601	0.154	8	0.692	0.118	4
2017q4	0.774	0.0828	5	0.64	0.149	12	0.688	0.119	3
2018q1	0.778	0.0824	5	0.484	0.138	2	0.778	0.126	26
2018q2	0.776	0.0813	2	0.533	0.143	4	0.712	0.117	3
2018q3	0.776	0.082	2	0.583	0.145	4	0.687	0.118	2
2018q4	0.769	0.0802	0	0.622	0.142	7	0.676	0.12	3
2019q1	0.768	0.0813	2	0.466	0.141	4	0.726	0.116	10
2019q2	0.763	0.081	2	0.513	0.143	0	0.671	0.115	1
2019q3	0.757	0.0798	5	0.565	0.145	0	0.649	0.115	1
2019q4	0.759	0.0807	2	0.604	0.141	8	0.652	0.12	4
2020q1	0.766	0.0812	3	0.454	0.142	3	0.721	0.118	12
2020q2	0.777	0.0844	7	0.518	0.148	3	0.705	0.122	9
Overall	0.771	0.0820		0.546	0.156		0.706	0.126	

Table 6. Scale efficiency (SE) score by quarter

year	Intermediation approach			Operating approach			Value-added approach		
	Mean	SD	Efficient banks	Mean	SD	Efficient banks	Mean	SD	Efficient banks
2017q1	0.973	0.0428	3	0.882	0.131	1	0.959	0.0529	11
2017q2	0.972	0.0461	1	0.852	0.14	2	0.953	0.0582	2
2017q3	0.972	0.0468	0	0.841	0.132	1	0.95	0.0643	0
2017q4	0.972	0.0441	1	0.863	0.112	4	0.946	0.0686	1
2018q1	0.973	0.0424	2	0.861	0.138	0	0.957	0.0536	11
2018q2	0.972	0.0437	2	0.831	0.142	2	0.953	0.0604	2
2018q3	0.971	0.0455	1	0.829	0.129	1	0.945	0.0687	1
2018q4	0.97	0.0449	0	0.856	0.11	1	0.938	0.0755	0
2019q1	0.971	0.0438	2	0.833	0.138	2	0.955	0.0564	6
2019q2	0.972	0.0423	1	0.821	0.135	1	0.945	0.0696	1
2019q3	0.972	0.0434	2	0.83	0.123	0	0.937	0.0779	1
2019q4	0.971	0.0438	2	0.857	0.104	4	0.93	0.0834	4
2020q1	0.971	0.0444	1	0.823	0.141	2	0.95	0.0643	6
2020q2	0.968	0.0461	2	0.816	0.140	1	0.946	0.0694	3
Overall	0.971	0.044		0.842	0.131		0.947	0.0670	

Tables 5 and 6 present PTE and SE estimates, respectively, under all three approaches. TE is obtained under the CRS assumption, while PTE is obtained under the VRS assumption. An agricultural bank is said to experience VRS, if the efficiency scores of the agricultural bank under these models are different (Avkiran, 1999). SE is derived by dividing TE by PTE. It is observed that both PTE and SE display a relatively stable pattern before and after the outbreak of Covid-19, under the three input-output combinations. The number of efficient agricultural banks varies differently under CRS and VRS assumptions. For example, 12 agricultural banks are found to be efficient under CRS in the first quarter of 2017, whereas the number is 32 under VRS. This evidence suggests the existence of sizable scale inefficiency among U.S. agricultural banks, as 20 banks failed to reach the CRS frontier.

5.2 The determinants of U.S. Agricultural banks' efficiency

5.2.1 Technical efficiency

Table 7 summarizes the regression results for the three approaches, where the TE scores obtained in the first stage are used as the dependent variables. All models here have good explanatory power. Most of the explanatory variables are statistically significant. However, the coefficient estimates vary under the different approaches.

Among the many explanatory variables, only NPL, LLPTL, and NETI are significant and have the same directional impacts on agricultural banks' TE scores, under all the approaches. The negative impact of NPL supports the conclusions from other studies that banks with low nonperforming loans are more efficient than those with high nonperforming loans (Abd Karim et al, 2010). LLPTL, loan loss provision to total loans, positively impacts agricultural banks' efficiency. It suggests that banks with higher confidence in controlling risk are actually more efficient. NETI, non-interest expense over total income, is used as a proxy for management quality. The negative relationship evidences the common sense that better management quality usually results in better efficiency level.

Loan portfolio composition (HERLOAN), which measures the banks' exposure to different industry sectors, has a significant, positive effect on TE scores, under the intermediation approach. This indicates that agricultural banks with a more concentrated loan structure tend to experience a higher level of efficiency. However, the coefficients are not significant under both the operating approach and the value-added approach. DTI, dividend payout ratio, shows a significant, positive relationship with TE scores under both the operating approach and the value-added approach. However, the coefficient is relatively small at 0.003.

For ETA, NITI, LNA and NIM, the same direction of impacts is revealed under the intermediation approach and the value-added approach, while the opposite direction of impacts is found under operating approach. Equity to asset (ETA) is introduced to measure capital adequacy. From table 7, the estimated coefficients are statistically significant for all three models. Under the intermediation approach and the value-added approach, the higher the bank capitalization, the lower the efficiency. However, the result is reversed under the operating approach. The natural logarithm of total assets (LNA) reveals a positive relationship with efficiencies under the intermediation approach and value-added approach. It indicates that agricultural banks with larger in size tend to be more efficient, although the coefficient is very small. However, it negatively affects efficiencies from the operating approach. Non-interest income over total income (NITI) measures agricultural banks' focus on traditional activities and exhibits a negative impact on efficiency levels under the intermediation approach and value-added approach. The direction of impact, however, is reversed under the operating approach. Net interest margin (NIM), an indicator of agricultural banks' long-run profitability, has significantly negative impacts under both the intermediation approach and the operating approach. Under the value-added approach, however, the relationship between NIM and TE is positive. Since operating approach mainly considers incomes, while the other two approaches focus on loans and investments in the output side, it is not surprising that operating approach and the other two approaches produce different results.

Table 7. Determinants of efficiency (TE)

		Intermediation approach		Operating approach		Value-added approach	
Variable	Explanation	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant		1.2464458***	0.0334236	0.3369112***	0.056924	0.941872***	0.045016
NPL	*Nonperforming Loan Ratio*	-0.1194652***	0.0332406	-0.2719412***	0.0566124	-0.375951***	0.04477
HERLOAN	*Loan portfolio structure*	0.0617178***	0.0116988	-0.0126985	0.0199243	0.024264	0.015756
ETA	*Equity to Asset*	-0.8965921***	0.0236532	0.4651052***	0.0402841	-1.949958***	0.031857
ROE	*Return on Equity*	-0.0492537**	0.0181994	0.2115762***	0.0309956	0.069873**	0.024512
LLPTL	*Loan quality*	0.5196006*	0.2182552	3.1381904***	0.3717127	2.028641***	0.293954
NITI	*Noninterest Income to Total Income*	-0.1241693***	0.0119163	0.6346841***	0.0202948	-0.188418***	0.016049
LTA	*Loans to Assets*	-0.2320411***	0.0052543	-0.0816877***	0.0089486	0.092697***	0.007077
NETI	*Noninterest Expense to Total Income*	-0.1375594***	0.007549	-0.3596364***	0.0128568	-0.204578***	0.010167
LNA	*Log of Assets*	0.0076945***	0.0010218	-0.0073923***	0.0017402	0.003278*	0.001376
LNGDP	*Log of GDP*	-0.0004743	0.0008793	0.0002796	0.0014976	0.002373*	0.001184
UEM	*Unemployment Rate*	-0.0426273	0.0553461	0.5160014***	0.0942605	0.210422**	0.074542
LNHPI	*Log of HPI*	-0.0429775***	0.004756	0.0398182***	0.0081001	0.007896	0.006406
DTI	*Dividend to Net income*	-0.0007951	0.0007482	0.0029827*	0.0012743	0.002238*	0.001008
NIM	*Net Interest Margin*	-0.2471949*	0.10254	3.8585423***	0.1746369	-4.275195***	0.138105
covid	*Covid Dummy*	-0.003115	0.0029245	-0.0510026***	0.0049807	-0.029507***	0.003939
R square		0.3326		0.3909		0.5232	
Adj R square		0.3311		0.3896		0.5222	
F stat		230.5		296.9		507.6	
N		6955		6955		6955	

Return on equity (ROE), another indicator for bank profitability, also has mixed impacts on TE scores. Under the operating approach and value-added approach, more profitable agricultural banks tend to have higher efficiency, which is in line with the findings of Isidro and Hassan (2002). However, the negative impact is observed under the intermediation approach. Banks with higher profitability may have more ability to take deposit, which can be a reason of lower efficiency under intermediation approach. But this needs further evidence. LTA, loans to asset, is used as a proxy of bank liquidity position. It shows a negative relationship with efficiencies under intermediation and operating approach, while a positive relationship is noted under the value-added approach.

Macroeconomic conditions do have significant impacts on agricultural banks' TE levels. The positive sign of LNGDP under value-added approach shows that agricultural banks tend to perform more efficiently under better economic conditions. Nevertheless, the sign of UEM is also positive under both operating approach and value-added approach. Which is not surprising since higher unemployment rate may suggest lower labor inputs in agricultural banks. The natural logarithm of the housing price index significantly negatively impacts efficiencies obtained from intermediation approach, but positively effects efficiencies calculated from the operating approach.

The Covid-19 variable has a negative impact on technical efficiencies under all three approaches, although the coefficient is not significant under the intermediation approach. Under the operating approach, Covid-19 decreased efficiency by about 5 percent for the expected TE level. For the value-added approach, the coefficient represents a decrease of about 3 percent. One possible reason is that Covid-19 impacts some operating methods more for U.S. agricultural banks (perhaps mitigated by arrangements to work from home), but not largely affecting the actual businesses. This suggests that the expense and income changed much more than other operating outcomes like loans and deposits. This would affect the TE more under the operating approach as compared to the other two approaches.

5.2.2 Pure technical efficiency and scale efficiency

The regression results for PTE are summarized in table 8. The estimates for PTE are very similar to the estimates for TE, except for the natural logarithm of total assets (LNA) in the operating approach. LNA reveals a positive relationship with efficiencies under operating efficiency for PTE, while the relationship is reversed for results of TE in table 7.

Table 8. Determinants of efficiency (PTE)

		Intermediation approach		Operating approach		Value-added approach	
Variable	Explanation	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant		0.994356***	0.0334236	0.0014658	0.062305	0.7107214***	0.0518653
NPL	*Nonperforming Loan Ratio*	-0.1220108**	0.0332406	-0.2053311***	0.0619639	-0.3961484***	0.0515814
HERLOAN	*Loan portfolio structure*	0.0424811**	0.0116988	-0.0485734*	0.0218077	0.0253605	0.0181537
ETA	*Equity to Asset*	-0.7698501***	0.0236532	0.5568434***	0.0440921	-1.5964609***	0.0367041
ROE	*Return on Equity*	-0.0335759	0.0181994	0.2490667***	0.0339256	0.0636087*	0.0282411
LLPTL	*Loan quality*	0.500866*	0.2182552	2.8761231***	0.4068502	1.9059391***	0.3386793
NITI	*Noninterest Income to Total Income*	-0.0749534***	0.0119163	0.5569464***	0.0222133	-0.1198869***	0.0184913
LTA	*Loans to Assets*	-0.1941769***	0.0052543	-0.0905099***	0.0097945	0.0861967***	0.0081534
NETI	*Noninterest Expense to Total Income*	-0.1092583***	0.007549	-0.3665996***	0.0140722	-0.1640662***	0.0117143
LNA	*Log of Assets*	0.0149989***	0.0010218	0.0328739***	0.0019047	0.011956***	0.0015855
LNGDP	*Log of GDP*	-0.0003148	0.0008793	-0.0020164	0.0016392	0.0011715	0.0013645
UEM	*Unemployment Rate*	0.0027564	0.0553461	0.5475603***	0.1031708	0.1706614*	0.0858837
LNHPI	*Log of HPI*	-0.0193546***	0.004756	0.0391571***	0.0088657	0.0276358***	0.0073802
DTI	*Dividend to Net income*	-0.0009802	0.0007482	0.0007005	0.0013948	0.0007158	0.0011611
NIM	*Net Interest Margin*	-0.3474272**	0.10254	4.4300677***	0.1911451	-4.1046621***	0.1591172
covid	*Covid Dummy*	-0.0045994	0.0029245	-0.04556***	0.0054515	-0.0287674***	0.0045381
R square		0.2296		0.4259		0.3946	
Adj R square		0.2279		0.4247		0.3933	
F stat		137.9		343.2		301.5	
N		6955		6955		6955	

Similar to table 7, the Covid-19 variable also have a negative impact on PTE under all three approaches. Under the operating approach, the Covid-19 decreased 4 to 5 percent from the expected PTE level. The estimate is about 3 percent under value-added approach. No significant impact is found under intermediation approach.

The estimates of SE determinants are summarized at Table 9, although the models do not have good explanatory power as that of TE and PTE. We can see that LNA has an opposite impact on SE for all the three approaches, compared to the PTE. In addition, ETA and ROE negatively affect SE but positively affect PTE under the operating approach. Both GDP and unemployment show no significant effects on SE for all three approaches. Compared to PTE, the housing price index has an opposite impact on SE for value-added approach. However, the negative impact of Covid-19 on SE is only significant under the operating approach.

Table 9. Determinants of efficiency (SE)

		Intermediation approach		Operating approach		Value-added approach	
Variable	Explanation	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant		1.2896896***	0.0334236	1.431207***	0.064554	1.2408027***	0.0331371
NPL	*Nonperforming Loan Ratio*	-0.003949	0.0332406	-0.171302**	0.064201	-0.0048516	0.0329557
HERLOAN	*Loan portfolio structure*	0.0221613**	0.0116988	0.030368	0.022595	-0.0010415	0.0115985
ETA	*Equity to Asset*	-0.176983***	0.0236532	-0.061548	0.045684	-0.6043807***	0.0234505
ROE	*Return on Equity*	-0.0183565	0.0181994	-0.004041	0.03515	0.0146656	0.0180435
LLPTL	*Loan quality*	0.0117864	0.2182552	0.809971.	0.421537	0.1886194	0.2163848
NITI	*Noninterest Income to Total Income*	-0.0596639***	0.0119163	0.216886***	0.023015	-0.0901038***	0.0118142
LTA	*Loans to Assets*	-0.0504837***	0.0052543	-0.013178	0.010148	0.013817**	0.0052092
NETI	*Noninterest Expense to Total Income*	-0.0321082***	0.007549	-0.058563***	0.01458	-0.0566607***	0.0074843
LNA	*Log of Assets*	-0.0075685***	0.0010218	-0.054878***	0.001973	-0.0063706***	0.001013
LNGDP	*Log of GDP*	-0.0004444	0.0008793	0.002116	0.001698	0.0012133	0.0008718
UEM	*Unemployment Rate*	-0.053187	0.0553461	0.110678	0.106895	0.0684186	0.0548717
LNHPI	*Log of HPI*	-0.0270571***	0.004756	0.005091	0.009186	-0.0211008***	0.0047153
DTI	*Dividend to Net income*	0.0001138	0.0007482	0.004663**	0.001445	0.0018117*	0.0007418
NIM	*Net Interest Margin*	0.1018492	0.10254	0.055428	0.198045	-0.4805539***	0.1016612
covid	*Covid Dummy*	0.0014664	0.0029245	-0.024715***	0.005648	-0.0020167	0.0028994
R square		0.08359		0.1335		0.122	
Adj R square		0.08161		0.1316		0.1201	
F stat		42.2		71.25		64.31	
N		6955		6955		6955	

6. **Summary**

This study employs input-oriented Data Envelopment analysis to investigate the efficiency of U.S. agricultural banks from the first quarter of 2017 to the second quarter of 2020. Three separate sets of inputs and outputs are employed: the intermediation approach, operating approach, and value-added approach. OLS is used in a second stage regression to study the impact of Covid-19 on operating efficiencies, after controlling for bank characteristics and the macroeconomic environment. One of the important implications for our study is that different choices of inputs and outputs may have different efficiency results. Therefore, employing only one set of input-output structure may be insufficient in efficiencies related studies.

The empirical findings suggest that U.S. agricultural banks are less than fully efficient under all three approaches of measuring inputs and outputs as different approaches produced divergent sets of efficiency estimates. The overall average technical efficiency score for the intermediation approach is about 74.76 %, with a quarterly average ranging from 73.5% to 75.6%. The estimated efficiency scores for the operating approach are lowest, at about 45.42%, while estimated efficiency scores for the value-added approach are around 66.73%. In addition, different findings of efficiency under assumptions of CRS and VRS technology suggest the existence of sizable scale inefficiency.

The multivariate regression results suggest that nonperforming loans ratio, loan loss provision to total loans, non-interest expense over total income, have significant and same directional impacts on agricultural banks' technical efficiency under all the approaches of measuring inputs and outputs. However, the other coefficient estimates vary for different approaches. The estimates for pure technical efficiency are very similar to the estimates for TE, except for the natural logarithm of total assets in the operating approach. LNA reveals a positive relationship with efficiencies under operating efficiency for PTE, while the relationship is reversed for results of TE. Additionally, the explanatory power for SE model is very low, compared to TE and PTE model, indicating that more potential variables needed to be included.

One central concern is with the impact of the Covid-19 outbreak. Our findings suggest that the shock from Covid-19 does have a significant and negative impact on all the technical efficiencies, pure technical efficiencies, and scale efficiencies, although the significance differs. For example, under the operating approach, Covid-19 reduced the expected TE level by about 5 percent. However, the impact under the value-added approach was about 3 percent, and it was not significant under the intermediation approach. Due to data limitations, the current study only uses first and second quarter data which aligns with the spread of Covid-19. The results might be improved after expanding the data period.

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