CREDIT RISK AND OPERATING EFFICIENCIES OF AGRICULTURAL AND NON-AGRICULTURAL BANKS DURING ECONOMIC RECESSIONS: A COMPARATIVE PERIOD ANALYSIS OF THE LATE 2000S GREAT RECESSION AND CURRENT PANDEMIC CONDITIONS

by

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(Under the Direction of Cesar L. Escalante & William Secor)

ABSTRACT

This dissertation examines how the financial health of U.S. agricultural banks and non-agricultural banks is impacted by the two major economic recessionary episodes experienced in the last two decades, namely the late 2000s Great Recession and the current Covid-19 pandemic condition.

The first of three studies analyze the relationship between loan sectoral distribution and banks' NPLs during different economic periods from 2004 to 2013, using a dynamic GMM model. Results suggest that, for non-agricultural banks, diversification in non-crisis years reduces NPLs, while specialization reduces NPLs during the financial crisis. The results also show that NPL levels in agricultural banks appear to be less responsive to the factors than non-agricultural banks. In particular, no impact from specialization was found for agricultural banks.

The second study employs a two-stage data envelopment analysis to study the impact of the current pandemic conditions on efficiencies of U.S. agricultural banks from the first quarter of 2017 to the second quarter of 2020. Three different sets of inputs and outputs are used: the intermediation approach, operating approach, and value-added approach. The empirical findings of this study suggest that U.S. agricultural banks are less than fully efficient under all three approaches of measuring inputs and outputs. Additionally, the results indicate 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.

The third study utilizes a two-step stochastic frontier analysis to investigate the cost efficiency of US agricultural and non-agricultural banks, through the period of 2004 to 2020. The findings suggest that the 2008 financial crisis have different impacts on agricultural banks and non-agricultural banks. The 2008 financial crisis significantly decreases the cost efficiency of non-agricultural by 0.55%. However, the impact is not significant for agricultural banks. The results also show that the Covid-19 pandemic actually increases the cost efficiency levels of both US agricultural banks and non-agricultural banks.

INDEX WORDS: Credit Risk, Stochastic Frontier Analysis, Data Envelopment Analysis, Dynamic Panel Data, Technical efficiency, Pure Technical Efficiency, Scale Efficiency, Agricultural Bank, Loan Concentration, Financial Crisis, Covid-19.

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DEDICATION

Dedicated to my parents, ZhongChen Gao and Jinlian Zhao, for their love and support

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CHAPTER 1

Introduction

During periods of financial crises when savings and equity funds tend to be quickly exhausted, banks are considered as the first resort for firms and individuals seeking financial assistance necessary to either sustain business operations or to avert adverse situations such as impending bankruptcies and unemployment. As such, the banks' lending operations could certainly exacerbate the level of credit risk they have to bear during periods of high economic volatility. Thus, it is very important to understand how the financial health of banks can be affected by shocks emanating from the prevailing macro environment.

In the last two decades, the U.S. economy had to deal with two significant economic downturns: the Great Recession of the Late 2000s and the current Covid-19 pandemic. Both crises struck the global economy with very serious economic repercussions. During the first financial crisis, the U.S. economy experienced high unemployment, declining real estate values, bankruptcies, and foreclosures, among many other indicators. For the second crisis, the one that the U. S. and global economies nowadays continue to deal with, the resulting reduction in economic activities caused by the lockdowns and a slump in consumer spending threatened the global financial system with another recession.

Both crises had significant impact on US commercial banks. The Great Recession, triggered by an increase in subprime mortgage defaults, which was first noted in February 2007, resulted in an abrupt increase in loan defaults and mortgage foreclosures that led to widespread crises in the banking industry (Brunnermeier, 2009). According to the Federal Deposit Insurance Corporation (FDIC), over 300 bank failures occurred during 2008 to 2010, including the famous Lehman Brothers. In contrast, only 24 bank failures were recorded during the 7-year period prior to 2007 (Li, Brewer& Escalante, 2018).

Although the Covid-19 pandemic does not have the same severe effect on the US banking system as the previous 2008 financial crisis, it does change US commercial banks in a number of ways. The resulting reduction in economic activities caused by the lockdowns and a slump in consumer spending threatened the global financial system with another recession. The equity returns of U.S. publicly traded firms whose headquarters are in an affected county were significantly and negatively affected compared to those whose headquarters are in non-Covid-19 counties (Bretscher et al., 2020). Another direct impact of the Covid-19 pandemic on banks is the increase in liquidity demand (Li, Strahan & Zhang, 2020; Chodorow-Reich et al., 2021). During the crisis, firms heavily incurred massive amount of debts from banks when facing deteriorating funding conditions.

In this regard, this study analyzes the effect of an economic recession on the quality of banks' loan portfolios and operating efficiencies. An additional dimension of this study's empirical framework is the focus on the bank specialization factor. Specifically, this study looks at a dichotomy of agricultural banks and their non-agricultural banking peers. Agricultural banks, unlike non-agricultural commercial banks, are usually relatively smaller with 90 percent being categorized as small banks, and most of them operate in rural areas. Their distinctly different operating environment suggests that operating trends, business strategies and other general findings associated with commercial banks may not necessarily hold for agricultural banks.

Even under normal circumstances, farm borrowers are usually regarded with more cautious and stringent considerations given the exposure and vulnerability of farm operations to sources of risk greater in magnitude and intensity than those experienced by non-farm businesses. Hence, when periods of economic hardships prevail, farm loan accommodations could even be harder to obtain. Drawing from the lessons of the farm crises of the 1980s, it was evident that significant loan exposures to agricultural activities increased the probability of bank failure.

To the best of our knowledge, there is limited research work done on the comparative analyses of the impact of the two major economic crises on the banking industry. The effects of these two crises on the performances of agricultural banks and non-agricultural banks are even more largely unexplored.

This dissertation mainly addresses two different broad issues, nonperforming loans and efficiencies, as applied to both the agricultural and non-agricultural banking sectors, under the backdrops of the two most recent economic recessions (the later 2000s Great Recession and the current Pandemic-induced economic downturn). The dissertation contains five chapters with the beginning and ending chapters providing and wrapping up, respectively, this study's research goals and objectives. In-between these sections are three related major empirical studies that look at different facets of banking operations using different analytical methodologies.

The first study, presented as Chapter 2, investigates the determinants of non-performing loans (NPL) of regular non-agricultural and specialized agricultural banks, with a specific focus on loan portfolio concentration. The analysis focuses on how much of a bank's delinquency situation (measured by its NPL portfolio) can be attributed to the concentration or diversification of its credit portfolio. In this approach, a generalized method of moments (GMM) dynamic panel data model is developed to consider the time persistence of NPLs. The essential idea of the method is based on the first-differences technique. After taking the first-differences transformation of the data, the unobserved bank-specific effects are removed, and lagged values of endogenous variables can be used as instruments in the first-differenced equation. To test the robustness of the results, we change key variable settings to determine if the results change significantly. Unstable results are likely to be affected by the changing of variable settings. In this step, we add a new variable of cash dividend to net income into the system. We also change the loans to assets ratio into loans to deposits ratio. Additionally, we use the assets per office as bank size instead of assets of a whole bank.

The second study, presented in Chapter 3, examines technical efficiencies of US agricultural banks using a nonparametric Data Envelopment Analysis (DEA) approach. Compared to other parametric methodologies, DEA does not require an explicit specification of the functional form of underlying production relationships, and it allows multiple inputs and outputs. Combined these attributes make it an attractive method. Unlike many other studies, this study employs three different approaches in defining agricultural banks' inputs and outputs to thoroughly evaluate efficiency: the intermediation, operating, and value-added approaches. To investigate the impacts of an economic recession shock, a second-stage multivariate regression is used, after controlling for bank-specific characteristics and macroeconomic conditions.

In the third study, presented in Chapter 4, a stochastic frontier efficiency model is developed to compare cost efficiencies of both US agricultural and non-agricultural banks during two episodes of economic recessions in the late 2000s and during the current pandemic. This analysis will identify specific operating strategies that either improve operating efficiencies or those that actually contribute to increased financial stress that need to be remedied.

CHAPTER 2

NPL: The Difference Between Agricultural and Non-Agricultural Lenders

2.1 Introduction

Deterioration in banks' loan portfolio quality can significantly affect the business viability of a banking institution. Nonperforming loans (NPLs) provide a measure of a bank's loan portfolio quality. As an important measure of the quality of loan portfolio, some analysts label NPLs as "financial pollution" because of their severe adverse economic consequences (Barseghyan, 2010).

Determining the important drivers of NPLs can help assess and forecast potential deteriorations in lending portfolio quality, which may help avert any impending internal financial turmoil, especially when the external economy is also experiencing difficult financial episodes. One important determinant of NPLs is lending specialization. Lending specialization captures the extent of diversification of the bank's risky assets – loans – among different loan types. Among other perspectives, policymakers have analyzed specialization by focusing on agricultural banks[1] (in contrast to general, commercial banks). Agricultural banks and non-agricultural banks have many differences in operating strategies, as well as their operating environments. In contrast to many non-agricultural banks, agricultural banks are usually smaller and located in rural areas. During the financial crises, agricultural banks were found to have performed better (as measured

[1]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. This distinction is used in this analysis to define two subsets of banking observations: agricultural and non-agricultural banks.

by NPLs) compared to their non-agricultural banking peers. This, therefore, motivates a closer scrutiny of the differences in these banks' operating strategies and credit risk management.

This paper answers the following questions. First, does specialization affect NPL performance differently during periods of economic growth, contrasted with the effects realized under an economic recession? Second, how does the impact of specialization and other NPL determinants differ for agricultural banks compared to non-agricultural banks? Other research has shown varying returns to specialization in the U.S. and elsewhere. Often specialization is characterized by the degree of loan concentration across several clientele sectors. This study incorporates the degree of specialization within specific industries (i.e., loan concentration quotients), while also using traditional measures of specialization (i.e., Hirschman-Herfindahl Index). This study uses more recent data, makes comparisons across agricultural and commercial banks, and is focused on NPLs as opposed to other performance metrics such as profitability or efficiency.

2.2 Literature Review

2.2.1 Determinants of NPL ratio

As a proxy for banks' credit risk exposure, issues surrounding NPL have received considerable attention because of the several downturns recorded in recent decades. Research includes both cross-country models and country-specific analyses. Several empirical studies identify the determinants of NPL ratio, and this body of literature generally agrees on a set of factors that consistently affect the banks' NPL. These factors can be categorized as banking-specific determinants (such as size, funding level, loan structure, and profitability) and macroeconomic determinants (such as GDP growth, unemployment rate, inflation rate, and interest rate).

The macroeconomic determinants argument is bolstered by the financial accelerator theory (Bernanke et al., 1989) contending that conditions in the economy and financial markets may reinforce each other. Skarica (2014) analyzed quarterly data from the third quarter of 2007 to the third quarter of 2012 in seven Central and Eastern European (CEE) countries. His findings indicate that a high NPL ratio may be a result of economic slowdown, as deduced from significantly large coefficients on such variables as GDP, unemployment, and the inflation rate. Similar results are derived by Jakubik and Reininger (2013), Messai and Jouini (2013), and Makri et al. (2014) when using different datasets in different regions. Ghosh (2015) studies all US commercial banks and savings institutions for 1984–2013. He finds that both banking-specific determinants (e.g. capitalization, liquidity risks, credit quality, cost inefficiency, and banking industry size) and macroeconomic determinants (e.g. state real GDP, real personal income growth rates, changes in state housing price indices, unemployment rates, and public debt) significantly impact NPLs. Saba et al. (2012) also reach similar results by using a similar period of data.

A number of studies focus on how banking-specific variables can also directly affect a bank's financial health and reflect its operating strategies. Tarchouna et al. (2017) find that small banks with a sound corporate governance system, a bank-specific variable, tends to have lower NPLs. Tajik et al. (2015) investigate the determinants of different categories of NPLs, concluding that the dynamics of NPLs are significantly affected by house price fluctuations, although the magnitude of impact varies across different bank types and loan categories. In addition, Ellul and Yerramilli (2013) show that bank holding companies with a higher risk management index have lower NPLs when analyzing all bank holding companies in the US from 1995 to 2010. Using a sample of publicly-traded bank holding companies in the US in 1994 –

2015, Ha (2020) studies the effect of conditional conservatism on loan loss accounting. The results indicate that the sample banks have lower NPLs when adopting conservative loan loss accounting practices, and conservative reporting reduces banks' risk-taking in lending.

2.2.2 Credit portfolio diversification

There are two main theories about the credit portfolio diversification effect. One theory presents the risk reduction argument of diversification. Based on the theory of asymmetric information, Diamond (1984) states that banks can transform monitored debt into unmonitored debt from diversification. This occurs because providing loans to different sectors can reduce the probability of default, and banks with less diversified loan structures are more vulnerable to an economic shock. Using a dataset containing the 2001-2002 Argentine financial crises, Bebczuk and Galindo (2008) show that diversification in the Argentine banking sector has a positive impact on both bank profitability and risk mitigation, and the impact is stronger during the economic downturn. The results of Rossi et al. (2009) also provide empirical support using the dataset of Austrian commercial banks during 1997-2003. They conclude that diversification harms cost efficiency, but it increases banks' profit efficiency and reduces risk.

The second theory contends that firms that concentrate their activities on a specific area can gain more expertise or knowledge in this area. Firms have a better understanding of controlling risk and reduce the likelihood of loan default (Meyer and Yeager, 2001). Supported by the theory of corporate finance, firms concentrating their activities on specific sectors would enjoy additional benefits from reduced costs (Acharya et al., 2006). By analyzing 105 Italian banks over the period 1993-1999, Acharya et al. (2016) find that diversification usually results in riskier loans for high-risk banks. Berger et al. (2010) study Chinese banks during 1996-2006 and conclude that more concentrated banks tend to perform better than banks with a high level of diversification. Similar results are also found in the Brazilian banking system (Tabak et al., 2011) and German banking sector (Hayden et al., 2007).

In this study, we investigate if there are different impacts of credit portfolio diversification based on the macroeconomic (i.e., during times of growth versus financial crisis) and on different types of banks, non-agricultural (diversified) banks and agricultural (specialized) banks, in the US.

2.2.3 Agricultural banking sector

Many lenders can corroborate the contention that financing agriculture can be both an opportunity and a challenge. The impact of changes in the agricultural economic environment is important to the delivery of credit to agriculture. One question among rural borrowers is how these changes affect the cost and availability of credit and bank services (Ellinger, 1994).

Featherstone and Moss (1994) study whether agricultural lending results in economies of diversification in U.S agricultural banks. Their results indicate little evidence for cost savings when expanding the share of agricultural lending. Featherstone (1996) examines the post-acquisition performance of rural banks and found that smaller banks and agricultural banks increased lending to agricultural sector after acquisition. The results also indicate that strong economies or diseconomies of scope do not exist for agricultural banks. Shen and Hartarska (2013) estimate the impact of financial derivatives, a risk management tool, on agricultural banks' profitability by using call report data from the Federal Reserve Bank of Chicago for the year 2006, 2008, and 2010. The results indicate that agricultural banks that use financial derivatives are less likely to be affected by credit and interest risk. Additionally, financial derivatives are an effective risk management tool during the sample period.

Kim and Katchova (2020) study the impact of the Basel III bank regulation on U.S. agricultural banks and non-agricultural banks. They find that agricultural loan volume is still increasing, although growth rates have slowed. They also find that the agricultural loan volume and the loan exposure to the agriculture sectors have decreased in regulated agricultural banks. Regmi et al. (2020) investigate the different effects of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 on big commercial banks and agricultural banks. They find that although the act has increased cost efficiency for large banks with more than $50 billion asset size, it reduced agricultural banks' cost efficiency. In addition, their results show that the act made productivity growth, efficiency, and technological changes slower in agricultural banks.

Another strand of research in the agricultural banking literature is to measure the efficiency and productivity to determine how management decisions and critical regulations impact the efficiency of bank operations. Many of these studies compare agricultural banks and non-agricultural banks and/or assess the impact of specialization on a particular outcome. For example, Dias and Helmers (2001) show that technical changes or innovation are the primary source of productivity for larger banks of both agricultural and non-agricultural banks, while small banks derive their competitive strength from increasing efficiency gains or catching up with frontier banks, by studying how post-deregulation (the Depository Institutions Deregulation and Monetary Control Act of 1980) structural changes have impacted agricultural banks and non-agricultural banks. The results of Yu et al. (2011) provide evidence that agricultural banks are more efficient under specialized lending operations. Li et al. (2018) assert 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.

Unlike other previous empirical studies devoted to agricultural banking, this paper mainly focuses on the differences in credit risk exposure between agricultural banks and non-agricultural banks, by investigating potential differences in the determinants of NPLs.

2.3 Methods

2.3.1 Dynamic panel data model

Following related earlier studies (Louzis et al., 2012; Tajik et al., 2015; Tarchouna et al., 2017), we use a GMM dynamic panel data model in this study to consider the time persistence of NPLs. The models are estimated separately for agricultural banks and non-agricultural banks.

We first consider the following model:

$$NPL_{i,t} = c + \alpha_1 NPL_{i,t-1} + \alpha_2 NPL_{i,t-2} + \beta BS_{i,t} + \eta Macro_{i,t}$$

$$+\gamma_1 \mathrm{HH}I_{i,t} + \sum_{j=2}^{5} \gamma_j LCQ_{i,jt} + \delta_0 \mathrm{crisis}_t + \epsilon_{i,t} \quad (2.1)$$

where $NPL_{i,t}$ is the nonperforming loan ratio of bank i at time t. On the right-hand side, α_i, β, η, γ_j, and δ_0 are vectors of parameters to be estimated. $NPL_{i,t-1}$ and $NPL_{i,t-2}$ are the one-period and two-period lags of bank i's NPL, respectively. $HHI_{i,t}$ is the loan portfolio concertation of bank i at time t. $LCQ_{i,jt}$ is the loan concentration quotients for loan sector j of bank i at time t. $BS_{i,t}$ is a vector of bank-specific variables of bank i at time t. $Macro_{i,t}$ is a vector of state-level macroeconomic variables. $Crisis_t$ is a dummy variable denoted as 1 to capture the period of financial crisis during the years 2007-2009.

To determine if loan portfolio concentration (HHI) and loan concentration quotients (LCQ) have different impacts during periods of contrasting economic conditions, i.e., financial crisis and non-crisis years, we then consider the following model with interactions:

$$NPL_{i,t} = c + \alpha_1 NPL_{i,t-1} + \alpha_2 NPL_{i,t-2} + \beta BS_{i,t} + \eta Macro_{i,t}$$

$$+\gamma_1 HHI_{i,t} + \sum_{j=2}^{5} \gamma_j LCQ_{i,jt} + \delta_1 \mathrm{HHI}_{\mathrm{i,t}} * c\mathrm{risis}_{\mathrm{t}}$$

$$+\delta_0 \mathrm{crisis}_{\mathrm{t}} + \sum_{j=2}^{5} \delta_j LCQ_{i,jt} * c\mathrm{risis}_{\mathrm{t}} + \epsilon_{i,t} \quad (2.2)$$

The presence of lagged dependent variables eliminates the panel data modeling alternative (e.g. OLS, fixed effects, and random effects model) since the lagged dependent variable is a function of the error term, which would then result in the typical panel data model estimates becoming inconsistent and biased.

Our first modeling alternative is using the generalized method of moments (GMM) estimator introduced by Arellano and Bond (1991). The essential idea of the method is based on the first-differences technique. After taking the first-differences transformation of the data, the unobserved bank-specific effects are removed. Then, lagged values of endogenous variables can be used to serve as instruments. However, Blundell and Bond (1998) point out that the first-differenced GMM estimator performs poorly if the instruments are weak. To deal with this issue, they propose the system GMM estimator which combines the standard first-differenced equations and an additional set of equations in level. In this analysis, we therefore follow Blundell and Bond (1998) using the system GMM estimator.

These GMM estimators require that instruments are exogenous. To test this, we use the Hansen over-identification test. Under the null hypothesis of the validity of the over-identification restrictions, the Hansen test statistics produce a χ^2 distribution. Rejection of the null hypothesis indicates that the restrictions are invalid. Furthermore, we apply the Arellano-Bond autocorrelation test, AR(1) and AR(2), to examine if there are first-order and second-order autocorrelations of the error terms in the first-differenced equation.

2.3.2 Variable description

This study uses NPL[2] (the ratio of total nonperforming loans to total loans) as the dependent variable. According to the Federal Reserve Bank of St. Louis, NPL is defined as loans past due for 90 days or more and still accruing interest plus non-accrual loans.

2.3.2.1 Loan portfolio concentration

In this analysis, loan portfolio concentration is measured using the Hirschman-Herfindahl Index (HHI). The index captures the extent of diversification of the bank's risky assets (loans) among different loan types. The index is constructed using the following loan classifications: real estate loans, agricultural loans, individual loans, and commercial & financial institution loans. The HHI for a bank in time t is calculated as the sum of the squares of different types of loan components:

$$\mathrm{HHI_{it}} = \sum(x_{it}^2) \tag{2.3}$$

Where x_{it} (ranges from 0-1) is the share of each loan sector to total loans for bank i at time t. The closer the HHI for a bank is to 1, the more concentration its loan portfolio.

To account for a bank loan portfolio's relative concentration in the different loan categories, loan concentration quotients are also calculated. The loan concentration quotients concept is borrowed from the location quotients concept in regional economics. It measures how concentrated a particular bank is in a particular industry compared to its peers. For this study, all banks operating in the same state are considered as an individual bank's peers. The formula for calculating the loan concentration quotient is as follows:

[2] Following the most commonly used definition, NPLs are calculated as the sum of total loans and leases labeled as delinquent (past due) for 90 days or more and loans considered as non-accrual divided by the total gross loan portfolio.

$$LCQ_{ijt} = \frac{x_{ijt}}{S_{jt}} \tag{2.4}$$

Where x_{ijt} is the share of bank i's loans that are in loan sector j at time t and S_{jt} is the share of all of the state's loans that are in loan sector j at time t. If this loan concentration quotient is over 1 for a particular sector, it indicates that the bank is more specialized or exposed to a particular category compared to the overall banking industry in its state.

Loan portfolio concentration (HHI) and loan concentration quotients (LCQ) measure two different aspects of loan structures. HHI reflects concentration in general. The LCQs reflect specialization within a specific industry and represents the bank's exposure to a particular industry. Combining these into the regression helps isolate the returns to specialization (the coefficient on HHI) while controlling for the particular issues from being concentrated in a particular industry. To the best of our knowledge, this is the first literature combining these two measures together.

2.3.2.2. Bank-specific variables

The bank-specific variables included in this analysis are bank size, loans to assets ratio, equity to asset ratio, the noninterest expense to total revenue ratio, the noninterest income to total income ratio, ROE, and insider loans ratio.

Bank size. Bank size is measured by the natural logarithm of total assets. There is a debate over the impact of bank size. On the one hand, bank sizes may increase NPLs due to the "too big to fail" argument where large banks may be inclined to take excessive risks by increasing their leverage and thus have higher NPL levels (Louzis et al., 2012). The flip side of this argument contends that larger banks may have more capacity to allocate or diversify their riskiness across its several operating sectors, therefore, reducing NPLs (Salas and Saurina, 2002).

Bank liquidity. We use the loans to assets ratio as a proxy for a bank's liquidity. When a bank has higher loans to assets ratio, it may realize a higher expected return but may be riskier as the probability of loan defaults could be higher. In addition, if the supply of loans increases, banks tend to lower their lending standards (Ghosh, 2015). We expect the coefficient to have a positive relationship with the dependent variable.

Operating efficiency. This measure takes into account both interest and noninterest expense categories. Interest expense represents the cost of borrowing money and trading account liabilities, among others. Non-interest expenses are incurred to sustain the bank's daily operations. Operating efficiency is measured by isolating noninterest expenses and dividing it by total revenue. Banks with higher operating expense ratios (lower operating efficiency) may have "bad management" issues and have poor credit monitoring techniques (Ghosh, 2015).

Bank profitability. The effect of bank profitability on NPLs is ambiguous. Intuitively, highly profitable banks have fewer incentives to engage in high-risk activities (Ghosh, 2015). Using the return on equity (ROE) as an indicator of bank performance, Godlewski (2004) shows that banks' profitability negatively impacts the level of NPL ratio. However, Garcia-Marco and Robles-Fernandez (2008) produce findings indicating that a higher level of ROE is usually followed by a higher insolvency risk among Spanish commercial banks operating from 1993 to 2000. The higher insolvency risk may in turn increase NPLs.

Capital strength. Capital strength is defined as total equity capital divided by total assets. Usually, a bank with a stronger capital base has lower default probabilities (Davis and Zhu, 2009). In addition, banks with low capital strength have more incentives to invest more in high-risk assets and consequently lower the loan quality (Salas and Saurina, 2002).

Moreover, we also analyze the bank's *noninterest activity ratio* (e.g., noninterest income to total income) and *insider loans ratio* (e.g., loans lent to insiders divided by total loans). The noninterest activity ratio provides us a closer look at a bank's income structure (Ghosh, 2015). The insider loans ratio can capture management risk in the form of fraud or insider abuse (Li and Escalante, 2016).

2.3.2.3 Macroeconomic variables

Macroeconomic growth rates directly impacts a bank's financial health. In a recession, borrowers' financial conditions most likely deteriorate as they face unexpected adverse economic shocks. Consequently, negative economic shocks could lead to a higher likelihood of loan defaults. Thus, we control annual GDP growth rate in our model.

Moreover, state unemployment rates are also used to provide additional indications of overall economic conditions. In addition, we also factor in a state housing price index into the model in consideration of the real estate industry's role in inducing recessionary conditions in the late 2000s.

2.3.3 Robustness check

To test the robustness of the results, we modify assumptions on certain variables to test their repercussions on the estimation results. Such variations include (a) introducing a new variable, cash dividend to net income; (b) replacing the loans to assets ratio variable with loans to deposits ratio; and (c) defining assets at the unit office level, instead of the entire banking business.

2.4 Data

Bank-level data are obtained from the Uniform Bank Performance Reports (UBPRs) that compile financial information for most FDIC-insured institutions. These data are available at Federal Financial Institutions Examination Council (FFIEC) Central Data Repository (CDR) Public Data Distribution (PDD) website. State GDP growth rates were 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). This dataset contains information for all 50 states and the District of Columbia from 2004 to 2013.

In order to exclude the impact of entry and exist, we only consider existing banks during the sample period to create a balanced panel setting. As U.S. commercial banks' sizes usually widely vary, we exclude banks with total assets larger than $1 billion, which is a widely accepted cutoff for separating large and small banks. This criterion ensures that the resulting banks in this study are of comparable business sizes. The final dataset consists of 459 agricultural banks and 3,325 non-agricultural banks, resulting in a total number of 37,840 observations.

The descriptive statistics of variables used in the analysis are shown in Table 2.1. During the sample time period, agricultural banks have a significantly lower NPL ratio than their non-agricultural banking peers. These two banking categories seem to have similar results for such variables as insider loan ratio and equity to asset ratio. The relative levels of the other variables, however, are significantly different at the one-percent significance level. On average, non-agricultural banks are larger than agricultural banks. The loan structure for agricultural banks is more diverse than non-agricultural banks. The loan to asset ratio is higher in non-agricultural banks, along with the noninterest expense to total revenue ratio and noninterest income to total income ratio. For agricultural banks, profitability is higher during this time period, as the ROE of agricultural banks is 10.6 compared to 8.9 in non-agricultural banks. The dataset also shows that agricultural banks are usually located in areas with better economic conditions than non-agricultural banks during the study's timeframe. This is deduced from the higher GDP growth rate, higher housing price change rate, and lower unemployment rate levels associated with the agricultural banking observations in our study's sample.

2.5 Results

2.5.1 Baseline results without interactions

Table 2.2 presents the results of the dynamic panel data model without interactions for agricultural banks and non-agricultural banks, respectively. The results show that loan portfolio concentration, operating strategies, and macroeconomic factors have different impacts on NPLs in agricultural banks and non-agricultural banks during the period from 2004 to 2013.

Validity

Table 2.2 contains the Hansen and Arellano-Bond tests of model validity. The Hansen p-values are larger than 0.1 indicating the validity of our instruments. AR (1) p-value and AR (2) p-value are the p-values from the Arellano-Bond tests for first and second order autocorrelation of the residuals, respectively. All requirements are met for these results, which indicates the estimates of our GMM results are consistent. The results show that the effect of lagged one year NPLs is positive and statistically significant at the 1% level for both types of banks, while the effect of lagged two year NPLs is not statistically significant for agricultural banks.

Loan Concentration

The loan portfolio concentration coefficient is positive and significant at the 1% level for non-agricultural banks. This finding is consistent with Diamond (1984), indicating that diversification in loan portfolio can reduce the possibility of defaults for non-agricultural banks. However, no such evidence was found for agricultural banks.

For non-agricultural banks, an increase of a bank loan portfolio's relative concentration in individual loans, compared to its peers in the same state, significantly decreases NPLs. The significantly positive coefficient on the loan concentration quotient for the commercial & financial institutional loan sector for non-agricultural banks indicates that such loans have increased relative risks than other types of loans. But both the results are not significant for agricultural banks.

Bank-specific Variables

An increase in bank size, measured by the natural logarithm of total assets, significantly increases NPLs for non-agricultural banks. This is consistent with the results reported by Louzis et al. (2012). In contrast, the bank size variable does not impact NPLs for agricultural banks.

The loans to assets ratio, measuring banks' liquidity, also have positive impacts on NPLs, as expected, in both agricultural and non-agricultural banks, and the coefficient is significant at the 1% significance level. As a bank increases its supply of loans, it has less liquidity. This result is consistent with Ghosh (2015).

The results in Table 2.2 also show that bank profitability has a significant, negative relationship with NPLs in both agricultural and non-agricultural banks, which indicates that banks with higher profitability tend to have lower credit risk. The insider loan ratio is negatively related to NPLs in non-agricultural banks, which supports the findings of La Porta et al. (2003). However, the ratio of insider loans shows no significant impacts on NPLs in agricultural banks. No significant relationships with NPLs are found in the other bank-specific variables for both types of banks.

Macroeconomic Variables

Among macroeconomic determinants, only unemployment rate has significant effects on NPL for both agricultural and non-agricultural banks. Lower unemployment rates result in lower NPL levels. Additionally, both state-level real GDP growth and housing price changes have a significantly negative relationship with NPLs in non-agricultural banks. A higher GDP growth and housing price index result in lower NPLs while the relationship is insignificant for agricultural banks.

In addition, external shocks from the financial crisis have a significant impact on both types of banks. Banks experienced higher NPLs during the crisis. The effect on agricultural banks is slightly higher than the effect validated among non-agricultural banks.

2.5.2 Baseline results with interactions

To further investigate the impact of loan portfolio structure across different economic conditions, we include the interaction terms of the loan concentration and financial crisis variables. The results of the dynamic panel data model for both bank types are presented in Table 2.3. It can be gleaned from the summary that most variables in Table2.2 have the same impact on NPLs in both agricultural banks and non-agricultural banks.

Similar to Table 2.2, all model validity requirements are still met, and the estimates of our GMM results are consistent. The results are the same for both bank-specific variables and macroeconomic variables obtained in Table 2.2. The only differences are noted among the loan structure variables.

The loan portfolio concentration coefficient is positive and significant at the 1% level for non-agricultural banks during the non-crisis years. Interestingly, the coefficient for the interaction term of crisis and HHI is negative and significant at the 5% level for non-agricultural banks. This suggests that focusing on fewer loan sectors during the financial crisis was a better strategy for non-agricultural banks to control credit risk. During the financial crisis, many sectors faced challenging economic and financial situations. Lending more loans to sectors that loan officers are more familiar with may have reduced credit risk. This is consistent with the findings from Meyer and Yeager (2001), Hayden et al. (2007), Berger et al. (2010), and Tabak et al. (2011). However, no benefit or penalty from specialization was validated among agricultural banks. The coefficients on HHI and the HHI-crisis interaction are both insignificant.

For non-agricultural banks, an increase in the loan concentration quotient for individual loans significantly decreases NPLs during both crisis and non-crisis years. The significant, negative coefficient of the loan concentration quotient in the real estate loan sector for non-agricultural banks during non-crisis years indicates that real estate loans had lower relative risks than other types of loans during non-crisis years in the study period. However, during the financial crisis period, lending more real estate loans increase NPLs, as evidenced by the significant, positive coefficient for the real estate loan concentration quotient-crisis interaction term. This is expected due to the significant drop in real estate values and subsequent loan defaults on real estate loans during the crisis. Loan concentration quotients in commercial and financial institutional loan sector does increase NPL levels during the non-crisis period, although it shows no significant impact on NPLs for nonagricultural banks for crisis years. One possible reason is that risk controlling is better in the sector during the financial crisis. In addition, lending more loans to the agricultural sector can decrease NPL levels for non-agricultural banks during the financial crisis. In contrast, the coefficient is insignificant for agricultural banks.

2.5.3 Robustness check

We run robustness checks to determine how stable the main results are. In this step, we add a new variable of the ratio of cash dividend to net income into the system. Additionally, we change the loans to assets ratio into loans to deposits ratio. Lastly, we also use the assets per office as bank size instead of assets of a whole bank. The results are presented in Table 2.4.

The new variables produced results consistent with those obtained from the original model in this analysis, although some slight changes in the significance levels change are noted for some variables. Nonetheless, the results indicate that our original estimates are robust. For example, the coefficient of loan portfolio concentration is positive and significant at 1% level to NPLs, while the coefficient is negative and significant at 5% level for non-agricultural banks in the financial crisis. Loan portfolio concentration is still not a very significant determinant for agricultural banks, the significance level is only about 10%. In addition, the coefficient on the HHI-crisis interaction is still significant for non-agricultural banks.

After we change the measurement of assets of a whole bank into assets per office of a bank, the estimate of the size variable is still positive and significant at 1% level for non-agricultural banks, which is in agreement with the assumption of "too big to fail". Indeed, large banks take excessive risks by increasing their leverage and thus have higher NPL levels. The new size variable remains insignificant for agricultural banks. The estimate of the loans to deposits ratio is similar to the estimates of the loans to assets ratio for agricultural banks, although it became insignificant for non-agricultural banks. In addition, the estimates of the new variable, cash dividend to net income, is positive and statistically significant at 10% level for non-agricultural banks, but the magnitude is small. Overall, our model performs well and appears to be robust to alternative specifications.

2.6 Conclusion

Determining the drivers of NPLs is of importance for both banks and policy makers to assess and forecast potential deteriorations in lending portfolio quality. To avert internal financial turmoil, especially when facing difficult economic periods, one important strategy is specialization or diversification in loan structures. In this paper, we investigate the relationship between loan sectoral distribution and banks' NPLs during different economic periods from 2004 to 2013. Different from previous literatures, this study incorporates the degree of specialization within specific industries (i.e., loan concentration quotients), while also using traditional measures of specialization (i.e., Hirschman-Herfindahl Index). Additionally, we also study the impact of lending specialization and other NPL determinants differ for agricultural banks compared to non-agricultural banks. The dynamic panel data GMM model was adopted in this paper.

Several notable results are validated in this analysis. We confirmed the results from previous literature that lending specialization does have significant impact on banks' credit risk. For non-agricultural banks, after controlling for industry-specific exposure, we find that diversification in non-crisis years reduces NPLs, while specialization reduces NPLs during the financial crisis. This finding in non-crisis years is consistent with the findings of Diamond (1984) indicating that diversification in loan portfolio can reduce the possibility of defaults for non-agricultural banks. However, during the financial crisis, it may be that lending more loans to sectors that loan officers are more familiar with may reduce credit risk. This is consistent with the findings from Meyer and Yeager (2001), Hayden et al. (2007) Berger et al. (2010), and Tabak et al. (2011).

We also find the different patterns in agricultural and non-agricultural banks. Overall, NPL levels in agricultural banks appear to be less responsive to the factors used in the analysis relative to these variables' validated effects on non-agricultural banks. In particular, agricultural banks see no impact from specialization. This may be due to their unique position in the industry as an agricultural bank, or strategies in managing credit risk.

The paper equips bank managers with a better understanding of the relationship between loan portfolio structure and NPLs. It sheds light on the role of lending specialization in the amelioration of loan quality and protection of U.S. banks from the impact of economic crisis. Our research also offers important implications and insights on credit risk controlling mechanisms for regulators and policy makers as they formulate resolutions to guide banks' loan portfolio structure decisions on diversification and specialization under different economic conditions. This paper also provides evidence of important differences of credit risk exposure between agricultural banks and non-agricultural banks, and demonstrates how these banks' operating strategies, with a specific focus on loan portfolio concentration, can variably affect the viability of these two banking categories.

The paper can be extended by incorporating different macroeconomic events, since NPLs, like many other variables measuring banks' performance, may be affected differently by different macroeconomic conditions. Additionally, in this study, non-agricultural banks are defined as banks with total assets under $1 billion, which is still a diverse, broad group. A closer look at different size ranges in the future may also provide valuable information.

Table 2.1. Variable descriptive statistics

	Non-agricultural banks				Agricultural banks				All Banks			
Variable	n	mean	sd	median	n	mean	sd	median	n	mean	sd	median
NPL (%)	33250	1.67	2.08	1	4590	1.15	1.5	0.68	37840	1.61	2.02	0.96
Asset ($000)	33250	196306	177421	135283	4590	87758	91418	60004	37840	183139	173001	122755
HHI	33250	0.58	0.17	0.57	4590	0.36	0.06	0.36	37840	0.55	0.18	0.53
LCQ_Agri	33250	3.01	6.86	0.95	4590	9.49	13.56	3.93	37840	3.8	8.25	1.34
LCQ_Indiv	33250	1.38	1.79	0.95	4590	1.04	0.91	0.77	37840	1.34	1.71	0.92
LCQ_Comm	33250	0.79	0.61	0.66	4590	0.77	0.42	0.7	37840	0.79	0.59	0.67
LCQ_Real	33250	1.09	0.38	1.06	4590	0.68	0.23	0.69	37840	1.04	0.39	1.03
LTA	33250	0.62	0.15	0.64	4590	0.59	0.16	0.6	37840	0.61	0.15	0.63
NIETR	33250	0.04	0.54	0.03	4590	0.03	0.53	0.03	37840	0.04	0.54	0.03
NIITI	33250	0.16	0.14	0.15	4590	0.12	0.07	0.11	37840	0.16	0.14	0.14
ROE (%)	33250	8.9	12.57	8.96	4590	10.6	6.68	10.13	37840	9.11	12.03	9.12
INSIDER (%)	33250	0.01	0.01	0.01	4590	0.01	0.02	0.01	37840	0.01	0.01	0.01
ETA	33250	0.11	0.04	0.1	4590	0.12	0.04	0.11	37840	0.11	0.04	0.1
GDP_PCT (%)	33250	1.59	2.58	1.78	4590	2.43	3.12	2.35	37840	1.69	2.66	1.81
UNEMPLOY (%)	33250	6.46	2.02	6	4590	5	1.58	4.6	37840	6.28	2.03	5.8
HPI_PCT (%)	33250	1.34	5.18	0.55	4590	1.82	3.42	1.46	37840	1.4	5	0.81

Note: Variable defination: NPL = nonperforming loan ratio, Asset = total assets, HHI = Hirschman-Herfindahl Index, LCQ_Agri = LCQ for agricultural loans, LCQ_Indiv= LCQ for individual laons, LCQ_Comm=LCQ for commerical & Industrial insitution loans, LCQ_Real = LCQ for real estate loans, LTA = loans to asset ratio, NIETR = noninterest expense to total revenue, NIITI = noninterest income to total income, ROE = return to equity, INSIDER = insider loans to total loans ratio, ETA = equity to asset ratio, GDP_PCT = GDP growth rate, UNEMPLOY = unemployment rate, HPI_PCT= housing price index change rate

Table 2.2. GMM results between agricultural and non-agricultural banks – without interactions

	Agricultural banks	Nonagricultural banks
Variables	NPL	NPL
NPL-1	0.808***	0.870***
	(4.078)	(12.206)
NPL-2	-0.194	-0.166***
	(-1.245)	(-2.798)
HHI	-0.369	0.387***
	(-0.930)	(3.590)
LCQ_Agri	0.000	0.002
	(0.301)	(0.582)
LCQ_Indiv	-0.034	-0.016***
	(-1.328)	(-3.212)
LCQ_Real	0.050	-0.009
	(0.393)	(-0.315)
LCQ_Comm	0.044	0.089***
	(0.695)	(4.687)
log(Asset)	0.014	0.035**
	(0.415)	(2.116)
LTA	0.536***	0.409***
	(2.606)	(5.414)
NIETR	0.012	0.012
	(0.419)	(0.297)
NIITI	0.847	-0.121
	(1.269)	(-0.928)
ROE	-0.026***	-0.014*
	(-3.989)	(-1.684)
INSIDER	-2.161	-2.023***
	(-1.625)	(-2.860)
ETA	0.836	-0.480
	(1.051)	(-1.346)
GDP_PCT	-0.001	-0.011***
	(-0.262)	(-2.917)
UNEMPLOY	0.076***	0.059***
	(3.518)	(6.590)
HPI_PCT	0.011	-0.030***
	(0.966)	(-7.625)
CRISIS09	0.209***	0.163***
	(4.951)	(8.003)
N	3672	26600
Hansen p-value	0.369	0.244
AR(1) p-value	0.034	0.000
AR(2) p-value	0.774	0.184

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3. GMM results between Agricultural and non-agricultural banks

	Agricultural banks NPL	Nonagricultural banks NPL
NPL-1	0.802***	0.862***
	(4.068)	(12.140)
NPL-2	-0.189	-0.159***
	(-1.217)	(-2.688)
HHI	-0.633	0.487***
	(-1.464)	(4.278)
LCQ_Agri	0.001	0.005
	(0.581)	(1.631)
LCQ_Indiv	-0.041	-0.010*
	(-1.409)	(-1.716)
LCQ_Real	0.011	-0.077**
	(0.080)	(-2.208)
LCQ_Comm	-0.021	0.072***
	(-0.307)	(3.288)
log(Asset)	0.014	0.034**
	(0.412)	(2.059)
LTA	0.511**	0.400***
	(2.493)	(5.292)
NIETR	0.011	0.011
	(0.392)	(0.276)
NIITI	0.845	-0.122
	(1.265)	(-0.941)
ROE	-0.025***	-0.014*
	(-3.977)	(-1.679)
INSIDER	-2.107	-2.058***
	(-1.583)	(-2.903)
ETA	0.830	-0.472
	(1.056)	(-1.328)
GDP_PCT	-0.002	-0.011***
	(-0.320)	(-3.115)
UNEMPLOY	0.076***	0.058***
	(3.559)	(6.579)
HPI_PCT	0.011	-0.031***
	(1.011)	(-7.676)
CRISIS09	-0.241	0.086
	(-0.691)	(0.705)
CRISIS09 *HHI	0.794	-0.363**
	(1.157)	(-2.352)
CRISIS09 *LCQ_Agri	-0.004	-0.011***
	(-1.073)	(-3.757)
CRISIS09 *LCQ_Indiv	0.018	-0.015*
	(0.559)	(-1.937)
CRISIS09 *LCQ_Real	0.069	0.277***
	(0.318)	(2.868)
CRISIS09 *LCQ_Comm	0.180	0.058
	(1.334)	(1.445)
N	3672	26600
Hansen p-value	0.400	0.244
AR(1) p-value	0.034	0.000
AR(2) p-value	0.779	0.151

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4. GMM results of with different variables

	Agricultural banks	Nonagricultural banks
	NPL	NPL
NPL-1	0.796***	0.870***
	(4.021)	(12.226)
NPL-2	-0.182	-0.168***
	(-1.173)	(-2.836)
HHI	-0.729*	0.556***
	(-1.671)	(5.083)
LCQ_Agri	0.001	0.005*
	(0.667)	(1.666)
LCQ_Indiv	-0.038	-0.014**
	(-1.323)	(-2.308)
LCQ_Real	0.018	-0.070**
	(0.144)	(-2.037)
LCQ_Comm	-0.026	0.082***
	(-0.379)	(3.735)
log(AssetPO)	0.053	0.071***
	(1.090)	(3.074)
LTD	0.399**	0.075
	(2.465)	(1.374)
NIETR	0.012	0.011
	(0.421)	(0.264)
NIITI	0.836	-0.122
	(1.264)	(-0.947)
DTNI	-0.000	0.006*
	(-0.010)	(1.778)
ROE	-0.026***	-0.014*
	(-4.026)	(-1.672)
INSIDER	-2.110	-1.739**
	(-1.594)	(-2.438)
ETA	0.487	-0.987***
	(0.624)	(-2.871)
GDP_PCT	-0.002	-0.012***
	(-0.298)	(-3.296)
UNEMPLOY	0.075***	0.056***
	(3.412)	(6.375)
HPI_PCT	0.011	-0.031***
	(0.981)	(-7.614)
CRISIS09	-0.246	0.095
	(-0.703)	(0.777)
CRISIS09 *HHI	0.789	-0.379**
	(1.146)	(-2.445)
CRISIS09 *LCQ_Agri	-0.004	-0.011***
	(-1.054)	(-3.772)
CRISIS09 *LCQ_Indiv	0.018	-0.016**
	(0.575)	(-1.989)
CRISIS09 *LCQ_Real	0.075	0.284***
	(0.347)	(2.913)
CRISIS09 *LCQ_Comm	0.181	0.056
	(1.347)	(1.366)
N	3672	26600
Hansen p-value	0.373	0.196
AR(1) p-value	0.035	0.000
AR(2) p-value	0.800	0.182

t statistics in parentheses. * p <0.1, ** p <0.05, *** p <0.01. AssetPO is Asset per office, LTD is loans to deposits ratio. DTNI is the ratio of cash dividend to net income

CHAPTER 3

U.S. Agricultural Banks' Efficiency Under COVID-19 Pandemic Conditions:

A Two-stage DEA Analysis

3.1 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.

3.2 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-term adverse effect of the crisis on Indian banks' profit efficiency. Mehdian, Rezvanian, and Stoica (2019) investigate the efficiency of large US commercial banks. Their results show that the efficiency of US large banks declined substantially during the Great Recession.

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 banks and identify sources of productivity growth in both agricultural and nonagricultural banks, by employing a DEA approach.[3] 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 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.

3.3 Methodology

3.3.1 *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.

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

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.[4] The technical efficiency of each DMU can be reached as a solution to the following optimization program:

$$min\ \theta$$

St: $$\sum_j \lambda_j X_{ij} \leq \theta X_{i0}$$

$$\sum_j \lambda_j Y_{rj} \geq Y_{r0}$$

$$\lambda_j \geq 0 \qquad (3.1)$$

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:

$$min\ \eta$$

St: $$\sum_j \lambda_j X_{ij} \leq \eta X_{i0}$$

$$\sum_j \lambda_j Y_{rj} \geq Y_{r0}$$

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

$$\sum \lambda_j = 1$$

$$\lambda_j \geq 0 \tag{3.2}$$

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 3.1.

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).

3.3.2 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:

$$Eff = a + b1\,Covid + b2\,Macros + \ b3B + e \tag{3.3}$$

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.

3.3.3 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 3.1.

3.4 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 3.2. Table 3.3 summarizes the second stage variables description and summary statistics.

3.5 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.

3.5.1 Efficiency of Agricultural banking sector

Table 3.4 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%. However, we see seasonality in operating approach and value-added approach. It is not surprising to see the seasonality, since the incomes and expenses are always highest in fourth quarter and lowest in first quarter in US banks. The seasonality suggests that neither operating approach nor value-added approach may be an ideal method in defining inputs and outputs for quarterly observations of US banks. With highest efficiency level in the first quarter under value-added approach does not have to mean that the bank in every first quarter is more efficient that other quarters.

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.

Tables 3.5 and 3.6 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.

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

3.5.2.1 Technical efficiency

Table 3.7 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 3.7, 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 the operating approach mainly considers incomes as its outputs, at the end of each year, the operating approach will produce the highest TE level, while the NIM is also the highest at the same time. It is not surprising that the operating approach and the other two approaches produce different results.

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. Under intermediation and operating approach, the higher the ratio, the lower its liquidity and riskier, indicates a bank is less efficient. But the relationship is inverse under 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.

3.5.2.2 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 3.7. It indicates that larger banks tend to more efficient than smaller ones in terms of PTE.

Similar to table 3.7, 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 3.9, 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. The larger a bank, the less scale efficient. In addition, ETA negatively affects SE, which means that a bank with higher equity ratio, thus more capability to repay its debt, has lower SE level. 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. The results show that there is negative relationship between the housing price and SE levels for banks. However, the negative impact of Covid-19 on SE is only significant under the operating approach.

3.6 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.

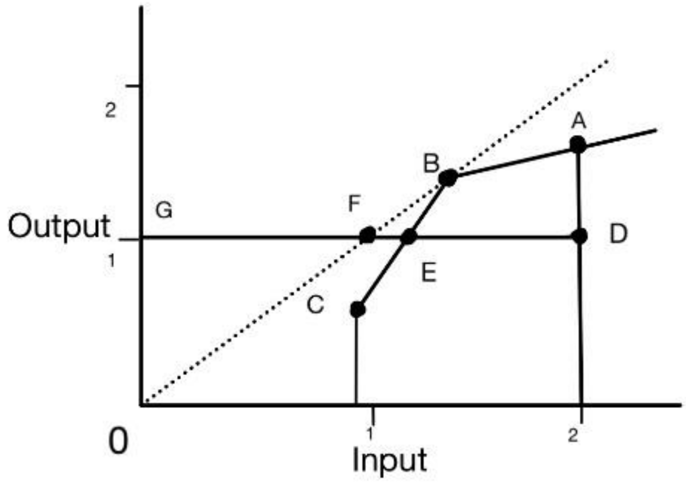

Figure 3.1. Comparison of CCR model and BCC model[5]

[5] The figure is a re-creation of Figure 4.3. from Cooper, Seiford and Tone (2007).

Table 3.1. 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

Table 3.2. 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 3.3. 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

Table 3.4. 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	

Table 3.5. Pure technical efficiency (PTE) score by quarter

	Intermediation approach			Operating approach			Value-added approach		
year	Mean	SD	Efficient banks	Mean	SD	Efficient banks	Mean	SD	Efficient banks
2017q1	0.778	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 3.6. Scale efficiency (SE) score by quarter

	Intermediation approach			Operating approach			Value-added approach		
year	Mean	SD	Efficient banks	Mean	SD	Efficient banks	Mean	SD	Efficient banks
2017q1	0.973	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	

Table 3.7. Determinants of efficiency (TE)

Variable	Explanation	Intermediation approach		Operating approach		Value-added approach	
		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	

Table 3.8. 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	

Table 3.9. 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	

CHAPTER 4

Banking Efficiency Analysis for U.S. Agricultural and Non-agricultural Banks: Comparative Period Analysis Between the Great Recession of the Late 2000s and the Current Pandemic Conditions

4.1 Introduction

In the last two decades, the U.S. economy had to deal with two significant economic downturns. The first general slowdown in economic activity occurred in the late 2000s. Labelled as the Great Recession of the Late 2000s, worsening global economic conditions began in December 2007 as declared by the National Bureau of Economic Research (NBER) that took cues from the deteriorating conditions in the labor market. The U.S. economy experienced high unemployment, declining real estate values, bankruptcies and foreclosures, among many other indicators. A widely accepted theory of the real culprit that significantly launched the onset of the economic crises in the United States was the breakdown of the real estate industry. The housing downturn started in 2006 when housing prices dropped significantly after reaching peak levels in the early 2000s. This resulted in an abrupt increase in loan defaults and mortgage foreclosures that led to widespread crises in the banking industry.

The second event is a more current one that the U.S. and global economies nowadays continue to deal with. Towards the end of 2019, the coronavirus (Covid-19) pandemic struck the global economy and altered social dynamics with very serious economic repercussions. 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, for example, real gross domestic product (GDP) decreased by 5.0 percent and 32.9 percent in the first and second quarters of 2020, respectively. The labor sector reported persistent unemployment conditions since the 1st quarter of 2020. The increased volatility of overall economic activity has caused serious concerns and prompted many mitigating actions from industry and government sectors.

The two both had significant impacts on US banking area. No matter during which crisis, banks are the first resort for firms and individuals when funding conditions deteriorate. When facing a potential bankruptcies or unemployment, borrowing loans from banks is usually their first choice. Certainly, the crises affected banks in many aspects. However, to the best of our knowledge, few of studies compare the different impacts of these two crises on banking area. And how these two crises affected performances between agricultural banks and non-agricultural banks differently is still an interesting question for us to answer.

In this study, we will mainly study how the efficiency for US agricultural and non-agricultural banks can be impacted by the two different crises happened in the last two decades: The Great Recession of the late 2000s and the current Covid-19 pandemic conditions. We have two reasons. First, the efficiency study in banking sector is of importance since improved efficiency will lead to increases in economic well-being and economic growth (Collender, 1994). In addition, banks with higher efficiency – more efficiently use available inputs to produce competitive products – have higher ability in long-term competitiveness (Ellinger, 1994). Given this, it is important to understand the determinants of banks efficiencies and how changes in market can improve overall banking efficiency. Second, we focus agricultural bank operations since as they are crucial to the success of the U.S. agricultural economy. And locating in different operating environment (usually smaller and located at rural areas), makes the general finding in commercial banks may not hold in agricultural banks.

In terms of methodology, we adopt a two-step approach. We use stochastic frontier analysis (SFA) model to measure banks efficiencies in the first stage. The efficiency can be measured in terms of cost efficiency, revenue efficiency, or profit efficiency. In this study, we use cost efficiency because it received the most attention in the US banking area, making the study more comparable. In the second stage, we use a dynamic panel data GMM approach to investigate how the two crises impacted the US agricultural and non-agricultural banks differently, after controlling other bank-specific variables and macro variables.

4.2 Literature Review

4.2.1 Frontier efficiency methodology

In measuring a bank's performance, both accounting ratio analysis and efficiency analysis are widely adopted in the current literature. However, efficiency studies gain increasing popularity due to its advantages in considering the importance of management or investment decisions (Sherman & Gold, 1985; Miah & Uddin, 2017). An increasing number of studies adopt the frontier efficiency methodology whereby the issue of how well a decision-making unit has fared could only be ascertained when analyzed in view of the relative performance of its peers faced with the same operating conditions and parameters. This evaluation method can help a bank's management determine if the bank is performing better or worse than its peers in terms of cost minimization, or profit maximization. As a very useful way in determining how a bank's performance, comparing to it peer, efficiency receives a wide discussion.

There are several different approaches in measuring banks' efficiencies. However, two approaches dominate the current literature: the Data Envelopment analysis (DEA) and the Stochastic Frontier Analysis (SFA). They are widely applied in the current financial institutions area. Ferrier and Lovell (1990) use both the SFA and DEA approaches to estimate the cost efficiency of U.S. banks. They found that the two approaches produce similar average cost efficiencies.

Berger and Mester (1997) discuss how stochastic frontier analysis is applied to analyze the performance of financial institutions by using three economic efficiency concepts: cost, standard profit, and alternative profit efficiencies. They find that each of these efficiency concepts has their own independent informational value. Mendes and Rebelo (1999) use the model to study efficiency, productivity and technological change among Portuguese banks during the period 1990 to 1995. Their results indicate the absence of any clear relationship between bank size and cost efficiency. Kumbhakar and Sarkar (2003) apply the stochastic cost frontier approach on Indian banks. They find that there is a tendency for inefficiencies to decline over time. Bos and Kolari (2005) employ both stochastic frontier cost and profit models to compare the efficiency between European and U.S. banks. Their results suggest that large US banks have higher profit efficiency on average.

Not only commercial banks, efficiency related studies for agricultural banks but also receive a lot of attention. The combined impact of changes in agricultural economy, technology advances, the competitive structure in the financial services industry and changing borrower demands is important to the delivery of credit to agriculture. A fundamental question among rural borrowers is how these changes affect the cost and availability of credit and bank services (Ellinger, 1994).

In the agricultural banks sector, Neff et al (1994) applied SFA method to measure both the cost inefficiency and profit inefficiency of US. agricultural banks. Their study finds that the estimates derived from the cost and profit frontiers are very different, where profit inefficiencies are found to account for a majority of total bank inefficiencies, and cost inefficiencies only be revealing a portion of the story. Dias and Helmers (2001) study how post-deregulation (the Depository Institutions Deregulation and Monetary Control Act of 1980) structural changes have impacted agricultural banks and identify sources of productivity growth in both agricultural and nonagricultural banks, by employing a DEA approach. They find that the primary source of productivity for larger banks of both agricultural and non-agricultural banks are technical changes or innovation, while small banks of both types derive their competitive strength from increasing efficiency gains or catching up with frontier banks. 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 survival banks were more technical efficient than failed banks, and banks with cheaper inputs are stronger in the financial crisis.

Choi, Stefanou and stokes (2007) apply both stochastic frontier analysis and data envelopment analysis, by using a balanced panel data set of 519 agricultural banks from 1996 to 2005. Their results suggest that agricultural bank's profitability is positively related to cost efficiencies. They also conclude that agricultural bank's efficiencies are negatively related to regulations, and larger agricultural banks are less efficient than smaller one.

Regmi et al (2020) investigate the difference impacts of too-big-to fail regulation (Dodd-Frank Wall Street Reform and Consumer Protection Act) on US agricultural banks and big banks, with a focus on cost efficiency and returns to scale measures. Their results indicate that the act reduced the cost efficiency of agricultural banks, although it increased cost efficiency for large banks with asset larger than $50 billion. They also conclude that the act encourages agricultural banks to specialize in agricultural lending.

4.2.2 The impact of Covid-19 on banking industry

Since the outbreak of Covid-19 pandemic, its direct impacts on different industries, especially banking area, receive lots of attention. The equity returns of U.S. publicly traded firms whose headquarters are in an affected county were significantly and negatively affected compared to those whose headquarters are in non-Covid-19 counties. The negative impact is stronger when Covid-19 cases are more intense (Bretscher et al., 2020).

One of the direct impacts of the Covid-19 pandemic on banks is the increase of liquidity demands. During the crisis, firms drew massive number of credits from banks when facing deteriorating funding conditions. However, Li et al (2020) find that most of the increase in liquidity demands were from largest banks during the pandemic. And the drawdowns on credits came mainly from large companies. Similar results were found by Chodorow-Reich et al (2021). Li et al (2020) also show that much larger increases in lending happens at banks closer to big outbreaks of the Covid-19. No significant relationship between banks' pre-crisis financial conditions and their lending.

During the Covid-19 pandemic, deposits in the US also increased dramatically from January 2020 to the end of 2020, with the increase of both personal saving rates and saving amount. Levine et al (2021) study the driving mechanism of the deposits and savings rates increase, by investigating US bank branches during the pandemic. Their results indicate that there is a strong positive relationship between deposits quantities at bank branches and local Covid-19 infection rates. However, deposits interest rates at branch level fall by more when facing higher Covid-19 infection rates, comparing to branches in lower infection rates counties. They also find that local Covid-19 infection rates intensify households' anxiety level, such as future job losses, income losses etc.

The impacts of the Covid-19 pandemic are also investigated in other economies. Korzeb and Niedziółka (2020) investigate resistance of Polish commercial banks to the Covid-19 pandemic. Their results show that banks with lower profitability and worse quality of credit portfolio are more sensitive than others, although the largest Polish commercial banks are the most resilient during the Covid-19 pandemic. In addition, the short-term effect of the pandemic impacts Polish bank sector by increasing the value of non-performing loans and write-offs dramatically. Barua and Barua (2021) study the impacts of the Covid-19 pandemic on three particular dimensions of banks - firm value, capital adequacy, and interest income - when facing different NPL shock scenarios, by studying Bangladesh's banking sector. Their findings suggest that risk-weighted asset values, capital adequacy ratios, and interest income are likely to fall, at both individual bank level and sectoral level, although larger banks are more vulnerable than smaller ones.

Borri and Di Giorgio (2021) investigate the systemic risk and the Covid-19 challenge in the European banking sector. During the Covid-19 period, their results suggest that European banks' contribution to systemic risk is significantly impacted by sovereign default risks. The covid-19 pandemic raises the debt levels and nonperforming loans in global banking system. Park and Shin (2021) study the impact of nonperforming loan ratios on global bank credit availability. Their results show that an increase in nonperforming loan ratios in both borrower and lender countries and higher banking outflows from emerging marketplaces are positively associated.

4.3 Methodology

4.3.1 Stochastic frontier analysis

The literature on banking efficiency analysis features two main frontier efficiency approaches, namely, stochastic frontier approach (SFA) and data envelopment analysis (DEA). SFA is a parametric econometric approach while the latter is a nonparametric linear programing approach. Compared with SFA, DEA approach does not require an explicit specification of the form of underlying production relationship. Nevertheless, the biggest disadvantage of DEA is that it does not allow random error. In other words, any variations will be seen as inefficiency if they are not from inputs (Miah & Uddin, 2017). Therefore, we use the parametric SFA approach which allows for random error. This is very important because it can be difficult to measure bank production due to data availability and different combinations of inputs and outputs (Bos & Kolari, 2005).

The efficiency can be measured in terms of cost efficiency, or profit efficiency. In this study, we use cost efficiency because it received the most attention in the US banking area. The cost frontier model is shown as follows:

$$C_{it} = f(p_{it}, Y_{it}, Z_{it}; \beta) + v_{it} + u_{it} \tag{4.1}$$

Where C_{it} is the total cost for bank i at time t; p_{it} represents input prices; Y_{it} is a vector of output quantities; Z_{it} are control variables; β is a vector of parameters to be estimated; v_{it} is the normal i.i.d. random error term with zero mean and variance σ_v^2; u_{it} measures cost inefficiency and follows the positive half normal distribution as $u_{it} \sim N^+(\mu, \sigma_u^2)$.

For the specification of the SFA model, the more flexible transcendental logarithmic (translog) cost function is used, since this specification produces a better fit of the frontier than the usual Cobb- Douglas function form, which holds the strong assumption that all banks have the same production elasticities (Kumbhakar and Lovell, 2000). The flexibility of the translog function helps to reduce the possibility of producing biased estimates from improper function form assumption. Therefore, our function can be specified as follows:

$$lnC = \beta_0 + \sum_{m=1}^{5} \beta_{ym} lny_m + 1/2 \sum_{m=1}^{5}\sum_{k=1}^{5} \beta_{ymk} ln\, y_m lny_k + \sum_{n=1}^{3} \beta_{pn}\, lnp_n$$

$$+1/2 \sum_{n=1}^{3}\sum_{l=1}^{3} \beta_{pnl} ln\, p_n lnp_l + \sum_{m=1}^{5}\sum_{n=1}^{3} \beta_{ypmn} ln\, y_m ln\, p_n$$

$$+\beta_t t + 1/2\beta_{tt} t^2 + v + u \qquad (4.2)$$

the number of outputs and input prices will be defined in the next section. t is a time trend which can capture the effect of technology change. The βs are the parameters to be estimated. Before estimating the cost frontier function, several necessary constraints need to be satisfied (Kumbhakar, Wang& Horncastle, 2015). The symmetric restrictions require that $\beta_{ymk} = \beta_{ykm}$ and $\beta_{pnl} = \beta_{pln}$. Aside from the symmetry restriction, a necessary condition of the cost frontier function is that homogeneous of degree one in the input prices. It has to satisfy the following restrictions: $\sum_{n=1}^{3} \beta_{pn} = 1$, $\sum_{n=1}^{3} \beta_{pnl} = 0$, $\sum_{n=1}^{3} \beta_{ypmn} = 0$. An easier way to impose the price homogeneity is to arbitrarily choose one input price and use it to normalize total cost and other prices. After imposing these restrictions, we get the following estimating form:

$$ln\left(\frac{C}{p3}\right) = \beta_0 + \sum_{m=1}^{5} \beta_{ym} lny_m + 1/2 \sum_{m=1}^{5} \beta_{ymm} lny_m{}^2 + \sum_{n=1}^{2} \beta_{pn}\, ln\left(\frac{p_n}{p_3}\right)$$

$$+1/2 \sum_{n=1}^{2} \beta_{pnn} ln\left(\frac{p_n}{p_3}\right)^2 + \sum_{m=1}^{5}\sum_{k=1,k>m}^{5} \beta_{ymk} ln\, y_m lny_k$$

$$+\sum_{n=1}^{2}\sum_{l=1,l>n}^{2}\beta_{pnl}ln\left(\frac{p_n}{p_3}\right)ln\left(\frac{p_l}{p_3}\right)+\sum_{m=1}^{5}\sum_{n=1}^{2}\beta_{ypmn}ln\,y_m ln\left(\frac{p_n}{p_3}\right)$$

$$+\beta_t t+1/2\beta_{tt}t^2+v+u \qquad (4.3)$$

All the estimators are estimated using the maximum likelihood approach. The cost efficiency of a bank is defined as $Eff_i = 1\ /\ exp(u)$, whose range is from 0 to 1. In addition, the cost efficiency model will be estimated using all the observations of agricultural and non-agricultural banks together.

4.3.2 Dynamic panel data model

In the second step, we study how the Covid-19 pandemic and the 2008 financial crisis impact cost efficiencies of both agricultural and non-agricultural banks. Following Otero et al. (2020), we use a GMM dynamic panel data model to consider the time persistence of cost efficiencies. The model in this analysis is specified by the following equation:

$$Eff_{it} = c + a1Eff_{it,-1} + b1Covid + b2Crisis + b3Macros_{i,t} + b4B_{i,t} + e_{it} \qquad (4.4)$$

Equation (4) models cost efficiency and its explanatory variables. Eff is the cost efficiency level from the first step. $Eff_{it,-1}$ is the one-year lag of bank i's cost efficiency at time t. B_{it} is a vector of bank-specific characteristics for each bank. $Macro_{it}$represents macroeconomic variables. c, a1, b1, b2 b3 and b4 are the parameters to be estimated. e_{it} is the i.i.d. random error term and normally distributed.

4.3.3 Description of variables

The selection of inputs and outputs is crucial in measuring a bank's efficiency and thus receives lots of discussion. However, no simple conclusion has been reached. There are many theories, such as production approach, intermediation approach, operating approach (also known as income approach), and value-added approach. The production approach and intermediation approach dominate the current literature. Under the production approach, banks are viewed as providers of services for account holders. Banks use physical inputs, such as labor, capital, and their costs, to produce different types of transactions, accounts, or documents for their customs. However, 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. Under the intermediation approach, banks are treated as financial intermediaries between borrowers and depositors. Banks purchase funds and collect deposits, and then, as an intermediary, they re-channel the money into loans and investments.

In this study, we use intermediation approach, as suggested by Berger and Humphrey (1997). We consider five outputs and three input prices. The outputs include total agricultural loans (y1), non-agricultural real estate loans (y2), other non-agricultural loans (y3), total investment (y4), and non-interest income (y5). Although the off-balance sheet (OBS) activities are non-earning assets, they are an important component in banks' core business. Failure to include the non-interest income activities will understate banks' outputs, and likely to statistically effect on bank's estimated efficiency (Siems, Clark, & Moore; 1997, Gulati & Kumar; 2016; Dong et al, 2016). Thus, we include non-interest income as our fifth output.

The input price vector consists of price of physical capital (p1) (calculated as occupancy expense divided by premises, fixed assets), price of borrowed fund (p2) (the ratio of total interest expense to the sum of deposits and other interest-bearing funding, price of labor (p3) (measured as average personnel expense per employee).

For the efficiency model, besides the dummy of indicating agricultural and non-agricultural banks, as well as the dummies of indicating the 2008 financial crisis and the 2019

Covid-19 pandemic, we control both macroeconomic variables and bank-specific variables to control heterogeneity and measure the determinants of the cost efficiencies. Macro economies can directly affect banks financial health. Consider the fact that most US banks operates within only one or a few states, banks tend to be more sensitive to regional conditions (Ghosh, 2015). Thus, we use state-level GDP growth, housing price change, state real personal income change, and unemployment rate to account for macroeconomic conditions. Bank-specific variables are also considered. To account for banks' overall conditions, we use a set of standard bank-level characteristics called CAMEL, following other literatures (Lambert et al., 2017; Bremus & Ludolph, 2021). CAMEL refers to bank's capital adequacy, asset quality, management, earning ability and liquidity. We use equity to asset ratio to measure banks' capital adequacy, loan loss provision over total loans to measure asset quality, noninterest expense over total income to measure management, net income over equity (ROE) to measure earning ability, and loans to deposit ratio to measure banks liquidity. We also include banks' total assets to control bank size. Besides, the following bank-specific variables, which may have potential impacts on banks' financial health, are included as well. These variables are nonperforming loans ratio, Herfindahl-Hirschman index (HHI), bank diversification, and dividend ratio. Nonperforming loans ratio are calculated as loans past due for 90 days or more and still accruing interest plus non-accrual loans, divided by total loans. HHI 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. Bank diversification is calculated as noninterest income divided by total income. 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. Thus, this variable allows us a closer look at a bank's income structure. The dividend ratio is calculated as dividend paid to shareholders over net income, which indicates how the bank values its investment in future growth, although may not directly reflect a bank's financial health.

4.4 Data

The paper contains both agricultural and non-agricultural banks in the United States, using both bank-level and macroeconomic data from 2004 to 2020 to measure the US banks' efficiencies. The bank-level data are obtained from the Reports of Income and Condition (Call Reports). In defining the 'agricultural banks', we use the common definition from Federal Deposit Insurance Corporation (FDIC), where a bank is defined as an agricultural bank if at least 25 percent of its total loan has been extended to the agricultural sector. We only examine surviving and healthy banks, that it, continuously operating banks during the sample period, to exclude the impact of entry and exit. The US commercial banks have a very wide range in their assets. To make the study more comparable, since almost all the agricultural banks have less than $1 billion assets, this paper excludes banks with larger than $1 billion, which is a commonly used threshold in defining large banks and small banks.

Macroeconomic data measures state-level economic activity, income, and asset value statistics. State GDP growth rates were 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). In addition, Covid-19 pandemic is a dummy defined as 2020, and the 2008 financial crisis is defined as a dummy of year 2007-2009.

The final data sample is a panel data with 451 agricultural and 2996 non-agricultural banks, with a total number of 58056 annual observations. The descriptive statistics of main variables are shown in Table 4.1.

4.5 Results

4.5.1 Cost Efficiency of U.S. Agricultural banks and Non-agricultural banks

The SFA model for both U.S. agricultural banks and non-agricultural banks are estimated using maximum likelihood techniques and the estimation results are summarized in Table 4.2. The rejection of likelihood ratio test (with Prob > χ^2= 0.0000) indicates the existence of inefficiency, supporting using of SFA model rather than standard OLS model. σ^2 is the sum of parameterized variance of $u \ and \ v$ as $\sigma^2 = \sigma_u^2 + \sigma_v^2$. $\gamma = \sigma_u^2/\sigma^2$, indicating the relative importance of inefficiency term. If u is zero, γ equals to zero and the SFA model is equal to OLS model. In contrast, when γ is 1, it means all deviations from the cost frontier can be explained by cost efficiency. Overall, our results indicate a good fit.

The results in Table 4.3 show that the mean cost efficiency levels for non-agricultural banks range from 83.4% to 88.5% from 2004 to 2020, while the range for agricultural banks is from 81.2% to 87.2%. On average, agricultural banks are less efficient than non-agricultural banks, with average cost levels of 84.9% and 85.9%, respectively. It indicates that during 2004-2020, agricultural and non-agricultural banks could have used 84.9% to 85.9% of their actual consumed inputs to produce the same level of outputs. However, the cost efficiencies of agricultural banks are higher than non-agricultural banks during the period of 2012-2014.

4.5.2 Regression Results

In this section we study the impacts of the Covid-19, the 2008 financial crisis and other determinants on cost efficiency of US Agricultural and non-agricultural banks. The results of the dynamic panel data model are summarized in Table 4.4. All requirements are met for the GMM models. The Hansen p-values are larger than 0.1 indicating the validity of our instruments. AR (1) p-value and AR (2) p-value are the p-values from the Arellano-Bond tests for first and second order autocorrelation of the residuals, respectively. Thus, the estimates of our GMM results are consistent. The results show that the effect of lagged one-year cost efficiency levels is positive and statistically significant at the 1% level for both types of commercial banks.

The results from Table 4.4 shows different impacts of the determinants on cost efficiency levels between the two types of commercial banks during the period of 2004-2020. Among the many variables, log asset, management, bank income structure, all the macroenvironmental variables, and the Covid-19 pandemic are significant and have same directional impacts on cost efficiency levels of US agricultural banks and non-agricultural banks. All the other determinants only have significant impacts on one type of commercial banks and remain insignificant for another type of commercial banks.

The log(asset) variable coefficient is negative and significant at the 1% level for both agricultural and non-agricultural banks. The finding is consistent with, Christopoulos, Lolos, & Tsionas (2002), Choi, Stefanou, & Stokes (2007) and Vu & Turnell (2011), indicating that larger banks, on average, seem to be less cost-efficient than their smaller peers.

Noninterest expense over total income, as a measurement of management quality, has a negative and significant impact on the cost efficiency of both types of banks. The banks with lower noninterest expense share of total income, indicating a better management quality, have a higher cost efficiency level. Noninterest income to total income, which is used to measure a bank's income structure, is positively and significantly associated with cost efficiency of both types of banks at 1% significance level. Thus, banks with more diversifications are more cost-efficient than those who focusing more on traditional interest-related banking activities.

Equity to asset (ETA), loans to deposits (LTD), and nonperforming loans ratio (NPL) remain significant for agricultural banks, while insignificant for non-agricultural banks. Capital adequacy, calculated as equity to asset, is negatively related to cost efficiency of agricultural banks. In other words, US agricultural banks with a lower capital level, thus, taking more risk, are more cost-efficient than those with higher capital ratios. This is consistent with the finding from Choi, Stefanou, & Stokes (2007), Lensink, Meesters, & Naaborg (2008), Vu & Turnell (2011), and Doan, Lin, & Doong (2018). Our results also show that bank liquidity, calculated as loans to deposits, has a negative effect on the cost efficiency of agricultural banks, which means that banks with more liquidity are more cost-efficient. In addition, we find that cost efficiencies of US agricultural banks are negatively and significantly impacted by nonperforming loans ratio.

The other variables, like asset quality (LLPTL), bank profitability (ROE), loan structure (HHI), and dividend payout ratio (DTI) have only significant effects on cost efficiency of non-agricultural banks. LLPTL, loan loss provision to total loans, negatively impacts non-agricultural banks' efficiency. It suggests that banks with lower loan loss provision to total loans, i.e. with better asset quality, are actually more efficient. The positive sign of bank profitability (return on equity) suggests that the non-agricultural banks with higher profitability tend to be more cost-efficient, although the magnitude is small. Banks with lower HHI means banks with a more diverse loan structure. The significantly positive coefficient indicates that non-agricultural banks with a more specialized loan structure tend to experience a higher level of efficiency. From the Table 4, we can also see that, DTI, dividend payout ratio, shows a significant, negative relationship with cost efficiency of non-agricultural banks.

All the macroeconomic variables have significant impacts on both the agricultural and non-agricultural banks, with same direction. Our results suggest that banks in an environment with higher GDP growth rate and unemployment rate, lower personal income growth and housing price index growth, are more cost-efficient.

One of our main goals is to compare the different impacts of the Covid-19 pandemic and the 2008 financial crisis on cost efficiency of US agricultural and non-agricultural banks. The results in Table 4.4 indicate that the 2008 financial crisis have different impacts of agricultural banks and non-agricultural banks. The 2008 financial crisis significantly decreases the cost efficiency of non-agricultural by 0.55%. However, the impact is not significant for agricultural banks. This contrasting result may be attributed to the agricultural banks' better position and strategies in managing credit risk, in addition to better economic conditions in the agricultural sector condition vis-a-vis other sectors in the economy (Hartarska and Nadolnyak, 2012).

Speaking of the impact of the Covid-19 pandemic, interestingly, our results show that it actually increases the cost efficiency levels of both US agricultural banks and non-agricultural banks. One possible reason could be that the pandemic is an outside shock to banks that responds. During the pandemic, more money was lent to businesses, which can increase outputs and efficiencies of banks. Another possible reason is that the Covid-19 pandemic only significantly affects some operating methods for U.S. banks, for example, working from home, but does not largely affect the actual businesses, so that the expense and income changed much more than other operating outcomes like loans and deposits, which in turn affects the efficiencies.

4.6 Conclusion

This study utilizes a two-step stochastic frontier analysis to investigate the cost efficiency of US agricultural and non-agricultural banks, through the period of 2004 to 2020. In the first stage, we employ the stochastic frontier function to measure the efficiency levels of the two types of commercial banks. The system GMM approach is used in the second step to compare the different impacts of the Covid-19 pandemic and the 2008 financial crisis on cost efficiency, obtained from the first stage, of agricultural and non-agricultural banks.

Our results show that both US agricultural and non-agricultural banks are less than fully efficient. Non-agricultural banks are more efficient than agricultural banks, with average cost efficiency levels of 85.9% and 84.9%, respectively. The mean cost efficiency levels for non-agricultural banks range from 83.4% to 88.5% from 2004 to 2020, while the range for agricultural banks is from 81.2% to 87.2%. We also show that the cost efficiencies of agricultural banks are higher than non-agricultural banks during the period of 2010-2014.

The second-stage results from the system GMM method suggest that log asset, management, bank income structure, all the macroenvironmental variables, and the Covid-19 pandemic are significant and have same directional impacts on cost efficiency levels of US agricultural banks and non-agricultural banks. All the other determinants only have significant impacts on one type of commercial banks and remain insignificant for another type of commercial banks.

Our findings also suggest that the 2008 financial crisis have different impacts on agricultural banks and non-agricultural banks. The 2008 financial crisis significantly decreases the cost efficiency of non-agricultural by 0.55%. However, the impact is not significant for agricultural banks. Our results also show that, interestingly, the Covid-19 pandemic actually increases the cost efficiency levels of both US agricultural banks and non-agricultural banks.

This article provides another insight into the impact of the Covid-19 pandemic on US banking sector, other than the traditional measurements like profitability, credit risk, etc. However, there are limitations of this study. First, due to the Covid-19 pandemic is still ongoing, we cannot access the whole impact of this pandemic. Results might be improved with more data. Second, our sample only covers banks with less than $1 billion assets. We do not include the large banks in our study.

Table 4.1. Descriptive statistics for inputs and outputs

		Agricultural banks		Non-agricultural banks	
		mean	sd	mean	sd
	Total cost	2744.26	3060.03	5494.3	5082.74
	Agri_loans	25312.91	30517.05	5044.62	9945.53
	RealE_loans	31540.33	45502.26	94012.34	94039.69
	Other_Loans	13724.18	19689.17	25362.47	30077.31
	Noninterest income	565.91	1021.21	1610.61	3867.86
	Total investment	32742.71	36970.81	56897.22	58228.14
	Physical capital price	0.64	1.9	0.37	1.08
	Fund price	0.07	0.02	0.07	0.02
First stage variables	Labor Price	64.95	16.31	61.76	18.71
	Asset	110085.19	124203.14	193999.4	162427.92
	Equitytoasset	0.12	0.04	0.11	0.04
	Loanquality	0	0.01	0	0.01
	Noninterestexpensetonetrevenue	0.58	0.12	0.63	0.18
	ROE	10.5	6.16	9.13	10.32
	Loanstodeposit	0.72	0.21	0.74	0.27
	Npl	0.01	0.02	0.01	0.02
	HHI	0.37	0.06	0.59	0.17
	Noninterestincometototalincome	0.03	0.02	0.05	0.03
	Dividendtonetincome	0.51	1.35	0.45	2.04
	GDP_pct	1.87	3.05	1.35	2.62
	Unemployment	4.56	1.54	5.79	1.98
	HPI_pct	2.8	3.01	2.6	4.29
Second stage variables	PI_pct	4.47	3.5	4.24	2.93

Table 4.2. Estimation results for the SFA function

Model Coefficients and Parameter Estimates			
Intercept	-1.527***	β_{yp12}	0.009***
	(0.254)		(0.001)
β_{y1}	0.025***	β_{y23}	0.001*
	(0.004)		(0.001)
β_{y2}	0.002	β_{y25}	-0.004***
	(0.011)		(0.001)
β_{y3}	0.411***	β_{y24}	-0.018***
	-0.02		(0.001)
β_{y4}	0.417***	β_{yp21}	-0.013***
	(0.024)		(0.001)
β_{y5}	-0.165***	β_{yp22}	0.019***
	(0.019)		(0.002)
β_{p1}	-0.231***	β_{y35}	0.017***
	(0.026)		(0.001)
β_{p2}	0.293***	β_{y34}	-0.041***
	(0.064)		(0.001)
β_{y11}	0.005***	β_{yp31}	-0.003**
	(0.000)		(0.001)
β_{y22}	0.065***	β_{yp32}	0.032***
	(0.001)		(0.003)
β_{y33}	0.021***	β_{y54}	-0.027***
	(0.001)		(0.001)
β_{y44}	0.097***	β_{yp51}	0.003**
	(0.002)		(0.001)
β_{y55}	0.008***	β_{yp52}	-0.062***
	(0.000)		(0.003)
β_{p11}	-0.028***	β_{yp41}	0.010***
	(0.002)		(0.002)
β_{p22}	0.076***	β_{yp42}	0.060***
	(0.010)		(0.004)
β_{y12}	-0.004***	β_{p12}	-0.018***
	(0.000)		(0.004)
β_{y13}	0.003***	β_{t}	-0.029***
	(0.000)		(0.000)
β_{y15}	-0.001**	β_{tt}	0.000***
	(0.000)		(0.000)
β_{y14}	0.003***	σ^2	0.086***
	(0.000)		(0.001)
β_{yp11}	-0.003***	γ	0.477***
	(0.000)		(0.013)

Table 4.3. Cost efficiency between agricultural and non-agricultural banks, 2004-2020

year	Non_Ag	Ag
2004	0.885	0.87
2005	0.877	0.86
2006	0.855	0.834
2007	0.834	0.812
2008	0.835	0.819
2009	0.843	0.838
2010	0.852	0.85
2011	0.86	0.859
2012	0.868	0.869
2013	0.87	0.871
2014	0.871	0.872
2015	0.871	0.869
2016	0.87	0.863
2017	0.867	0.857
2018	0.859	0.845
2019	0.843	0.824
2020	0.85	0.828
Average	0.859	0.849

Table 4.4. GMM results between agricultural and non-agricultural banks

	Agricultural Banks		Non-agricultural Banks	
Variables	Coef.	SE	Coef.	SE
Constant	0.2277***	0.054452	0.2385***	0.0266548
Eff-1	0.8704***	0.0478277	0.8302***	0.0246573
log(asset)	-0.0055***	0.0008767	-0.0053***	0.0003784
ETA	-0.0581***	0.0190155	-0.0136	0.0147379
LLPTL	-0.156	0.1092029	-0.2763***	0.0430668
NETI	-0.0976***	0.0116802	-0.086***	0.0043342
ROE	0.0000	0.0001699	0.0001***	0.0000232
LTD	-0.0055*	0.0028659	0.0005	0.0006433
NPL	-0.0895***	0.0269584	0.0065	0.0125507
HHI	-0.0111	0.0085005	0.0108***	0.0015006
NITI	0.2001***	0.0402357	0.0824***	0.014968
DTI	-0.0003	0.0002214	-0.0002***	0.0000626
GDP	0.0009***	0.0001704	0.0003***	0.0000724
HPI	-0.0012***	0.0002143	-0.0003***	0.0000633
UEM	0.0029***	0.0003396	0.0027***	0.0000973
PPI	-0.001***	0.000135	-0.0004***	0.0000495
CRISIS	-0.0014	0.0016434	-0.0055***	0.0005848
COVID	0.017***	0.002336	0.0089***	0.0008794
N	7163		47106	
Hansen p-value	0.874		0.136	
AR(1) p-value	0.000		0.000	
AR(2) p-value	0.457		0.896	

CHAPTER 5

Conclusion

This dissertation research features three separate studies that deal with the banking financial performance effects and implications of two important stressful economic episodes, the late 2000s Great Recession and an evolving recession under the pandemic. The analytical approach adopts a specific focus on the bank specialization factor through a comparative analyses of how agricultural banks and non-agricultural banks are impacted during the current economic predicament in the light of the lessons learned from the last recession. Despite the reality that we are actually still in the midst of the current pandemic, the repercussions of the prevailing modified social and economic environments have already been proven to have had substantial impacts on U.S. financial market, with numerous business closures and large-scale layoffs. Thus, the current research thrust offers potentially important contributions to both the agricultural finance literature and non-academic interest groups (including industry and policymaking sectors) that seek to understand and resolve impending economic issues.

The contributions of this dissertation research can be summarized as follows: First, it sheds light on notable differences of the quality of loan portfolios between those held by agricultural banks and non-agricultural banks. Moreover, it validates operating strategies, as well as macro-economic factors, can affect both types of banks differently. Second, it measures the extent of the economic and financial impacts of the modified social and economic environments during the Covid-19 pandemic on the U.S. financial market, with a specific focus on the agricultural banking sector. Finally, results of the analyses clarifies the differences in magnitude and relative extent of the economic and financial effects caused by the current pandemic and the last Great Recession.

The first study examines the relationship between loan sectoral distribution and banks' NPLs during different economic periods from 2004 to 2013. Compared to previous work undertaken in this area, this study incorporates the degree of specialization within specific industries (i.e., loan concentration quotients), while also using traditional measures of specialization (i.e., Hirschman-Herfindahl Index). Additionally, it studies the impact of lending specialization and other NPL determinants for agricultural banks compared to non-agricultural banks. The impact of the degree of specialization and other determinants on NPL is estimated using the dynamic panel data GMM model.

This study produced several notable results. For non-agricultural banks, after controlling for industry-specific exposure, it found that diversification in non-crisis years reduces NPLs, while specialization reduces NPLs during the financial crisis. It indicates that, during non-crisis years, diversification in loan portfolio can reduce the possibility of defaults for non-agricultural banks. However, during the financial crisis, it may be that lending more loans to sectors that loan officers are more familiar with may reduce credit risk. This study also found that NPL levels in agricultural banks appear to be less responsive to the factors used in the analysis relative to these variables' validated effects on non-agricultural banks. In particular, agricultural banks see no impact from specialization. This may be due to their unique position in the industry as an agricultural bank, or strategies in managing credit risk.

The second study analyzes the impact of the current pandemic conditions on efficiencies of U.S. agricultural banks from the first quarter of 2017 to the second quarter of 2020. A combination of the nonparametric input-oriented Data Envelopment analysis and the OLS is used in this study. This study employs three different sets of inputs and outputs: the intermediation approach, operating approach, and value-added approach. One of the important implications for this 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 measuring overall efficiencies.

The empirical findings of this study 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%. Additionally, the results indicate 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.

The third study utilizes a two-step stochastic frontier analysis to investigate the cost efficiency of US agricultural and non-agricultural banks, through the period of 2004 to 2020. The stochastic frontier approach is employed in the first stage and a dynamic GMM model is used in the second stage, to study the effects of the Covid-19 pandemic and the 2008 financial crisis on both agricultural and non-agricultural banks. The results indicate that non-agricultural banks are more efficient than agricultural banks, with average cost efficiency levels of 85.9% and 84.9%, respectively.

The findings also suggest that the 2008 financial crisis have different impacts on agricultural banks and non-agricultural banks. The 2008 financial crisis significantly decreases the cost efficiency of non-agricultural by 0.55%. However, the impact is not significant for agricultural banks. The results also show that, interestingly, the Covid-19 pandemic actually increases the cost efficiency levels of both US agricultural banks and non-agricultural banks.

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