NORTH DAKOTA BANKING EFFICIENCY: A DEA APPLICATION TO AGRICULTURAL AND NON-AGRICULTURAL BANKS PRE- AND POST-FINANCIAL CRISIS 2002-2012

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North Dakota Banking Efficiency: A DEA Application to Agricultural and Non-Agricultural Banks Pre- and Post-Financial Crisis 2002-2012

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

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ABSTRACT

The Great Recession of the late 2000s had negative economic impacts across the United States with unemployment rates rising, many bank failures, and other numerous economic problems. However, North Dakota was able to fend off the effects of the Great Recession by relying on their energy and agricultural industries during this time. North Dakota banks were able to avoid failure unlike many other banks in the nation during the recession. Empirical results of data envelopment analysis efficiency measurement shows that banks in North Dakota were able to increase efficiency from Q4:2002 to Q4:2012 without the recession having negative impacts on efficiency. Non-agricultural banks were more efficient in their production process when compared to agricultural banks.

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CHAPTER 1: INTRODUCTION

The United States economy experienced a significant slowdown in economic activity during the late 2000s. According to the National Bureau of Economic Research, the most recent recession started in December 2007 and ended in June 2009 (Hall *et al.* 2010). This was the worst and longest recession that the U.S. experienced since WWII lasting 18 months long. There were many different trends in the economy that occurred during this recession which included but was not limited to: declining real estate prices, high unemployment rates, bankruptcies and foreclosures of financial institutions as well as other private companies (Li 2011).

Acharya and Richardson (2009) found consensual agreement that the credit boom and housing bubble of the early 2000s caused the financial crisis. Housing prices grew to peaks during the early 2000s creating a "bubble" that when burst was sure to cause a severe economic crisis (Acharya & Richardson 2009). During this time, mortgages were approved for borrowers that had little ability to pay them, and these mortgages were securitized which allowed the credit markets to grow at a rapid pace. When housing prices started to drop in late 2007 and early 2008, many subprime mortgages went into default and created problems for the financial institutions that securitized and granted them. These institutions ran into capital adequacy problems along with liquidity and solvency problems.

As more banks ran into liquidity and solvency problems, the Federal Deposit Insurance Corporation (FDIC) predicted that there would be an increase in bank failures in the coming months of 2008 and readied themselves and took careful precaution in observing their "watch list" of problem banks (Li 2011). Between 2002 and 2007, the FDIC closed 21 banks that had failed. In 2008 there were 25 failed banks. However, these numbers increased significantly to 140 and 157 in 2009 and 2010 respectively (Corporation 2013). Georgia, Florida, Illinois, and

California led the states with the most failed banks at 52, 44, 39, and 36 respectively. There were a few states that did not have a bank fail between 2007 and 2010. These were Alaska, Connecticut, Hawaii, Maine, Montana, New Hampshire, North Dakota, Tennessee, and Vermont, and present unique areas to study.

North Dakota Economy

Even though the nation as a whole suffered from an economic downturn from 2007-2009, not every state experienced the same economic woes. North Dakota was a state that continuously stood out in the national economy as being a success during the recent financial crisis (Fried 2011). While the national economy took this downturn, North Dakota's economy thrived. North Dakota was the only state to have a budget surplus during this period. To add to the budget surplus, North Dakota also posted the lowest unemployment rates throughout most months during the crisis (Statistics 2013). As seen in Figure 1.1, North Dakota's unemployment rate remained steady between 3% and 4% which was well below the national average which varied between 7% and 10%.

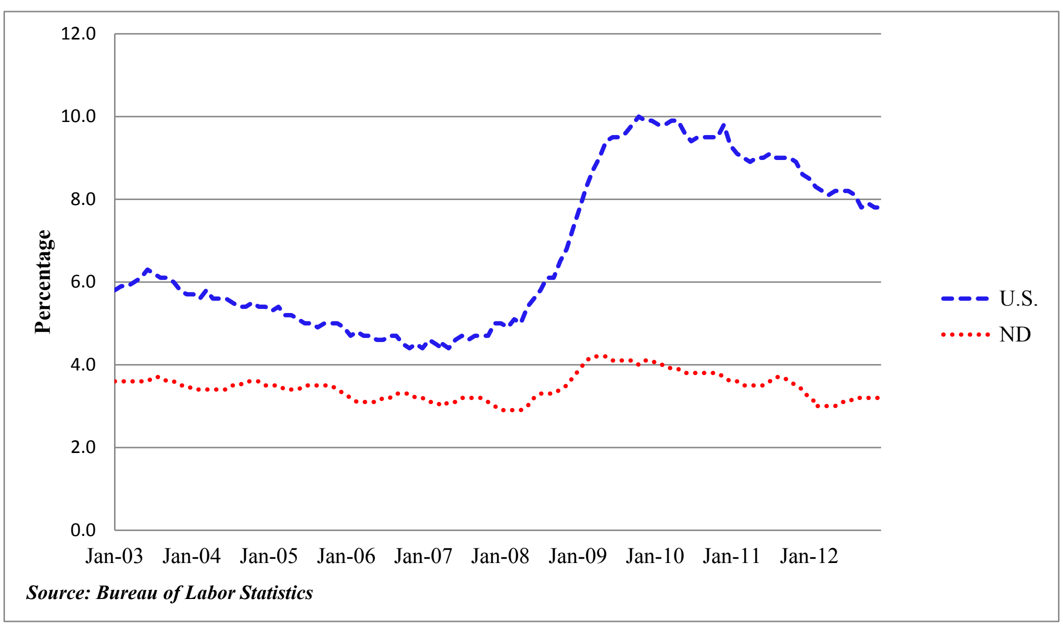


Figure 1.1 – Unemployment Rates

The economic success of North Dakota can be attributed to many different things. As some may say, some of the success in North Dakota can be attributed to political actions by the legislature (Calle 2012); however, this is not under the scope of this research and will not be discussed. More importantly, there are economic reasons to North Dakota's success. Two major reasons are the success of the energy/oil sector in North Dakota and also the state's agricultural sector.

Energy

The energy/oil sector experienced an increase in production during the financial crisis. In particular, the Bakken Formation was discovered in 1951, but in April 2008 the United States Geological Survey reported that 3.0 to 4.2 billion barrels of oil could be recovered from the shale formation (Geology.com). With this report came a major increase in the production of oil and natural gas in the western one-third of North Dakota. Due to the increase in production, there was an increased demand for labor to extract this available oil which helped keep the unemployment rate in North Dakota at low levels. The oil and natural gas industries support more than 46,000 jobs (Forum).

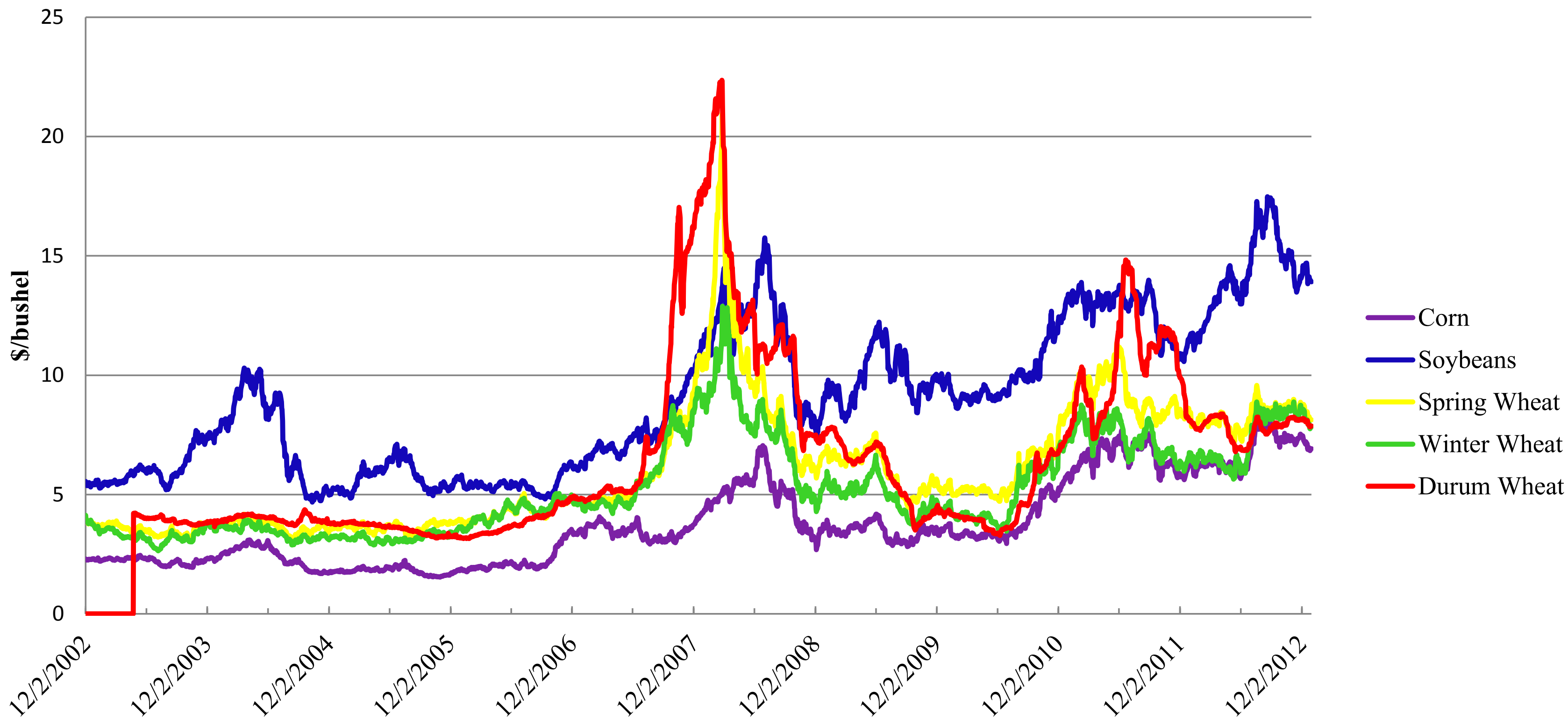
Not only was there an increase in oil production at this time, but there was a stable and slightly increasing production rate with other energy production in the state of North Dakota. Other areas of energy that North Dakota produces are lignite coal, wind, ethanol, biodiesel, and biomass. The wind energy sector alone has created more than 1,000 jobs in the recent years (Council). According to the National Mining Association, coal directly and indirectly accounted for around 12,000 jobs in North Dakota in 2011 (Association 2013). The four ethanol production plants help account for 10,000 jobs across the entire ethanol sector in North Dakota alone (Council). All of these sectors of energy production have been linked to the success of the North Dakota economy.

Agriculture

The other industry that has helped lead to the budget surplus in North Dakota is the agricultural industry which is the second leading industry in North Dakota after the oil and natural gas industry took over the number one spot in 2012. North Dakota is a leading producer of crops in the U.S. ranking in the top 15 states of the production of major U.S. crops. It is the number one producer of barley, wheat, and sunflowers. Additionally, according to 2012 production, North Dakota is the 7th highest producer of soybeans and the 8th ranked producer of corn (NASS, 2012).

The prices of the major crops produced in North Dakota and also the U.S. saw higher prices during and after the financial crisis than the period leading up to the crisis. At the start of the crisis in December 2007, corn and soybeans were experiencing high prices at the time. The price of corn was $4.06 per bushel on December 14, 2007 and the price of soybeans was $10.81 per bushel . Once the effects of the crisis started to be felt nationally in late 2008 then those prices started to decline but not below the price levels prior to December 2007. Corn and soybean prices again rose after the official end of the crisis and reached all-time highs in August 2012. Wheat prices continued to rise throughout the financial crisis and actually peaked in February 2008. Wheat prices then significantly fell but not below their pre-crisis levels. The price trends can be seen in Figure 2.

The higher prices of major crops led to higher revenue levels for all players in production of agricultural products. The most recognizable increase is obviously for the farmer/producer that sells the crops to the elevators. Yet, these higher commodity prices also increase the revenues for elevators and anyone included in the supply chain until the final product. These revenues are then reflected back into the state's own economy and help add to the state's revenues.



Sources: National Corn Historical Spot Index, National Soybean Historical Spot Index, Hard Red Spring Wheat Historical Spot Index, Hard Winter Wheat Historical Spot Index, Durum Wheat Historical Spot Index

Figure 1.2 – Grain Spot Prices

Research Objective

All of the above situations affect individual banks and the way they handle their everyday operations. Since North Dakota experienced low unemployment and strong economic activity between December 2007 and June 2009 while the nation experienced high unemployment rates and an economic/financial crisis, one has to wonder how the banks in North Dakota faired during this time period. Also, as stated earlier there was not a single North Dakota bank that failed during the crisis, but one has to wonder whether North Dakota banks were successful and efficient in their everyday activities during this time or if they simply did enough to just "stay afloat" and avoid going into the red. The main objective of this research is to evaluate the efficiency of North Dakota banks using data envelopment analysis (DEA). In addition, agricultural banks will be compared to non-agricultural banks. This is due to the fact that in most cases, even during strong economic times, agricultural lending is taken more cautiously because of the risks associated with agricultural production outside of the financial risks, i.e., weather risk, price volatility, insects, diseases, etc. Since the economic downturn caused lenders to be aware of the quality of loans they originated and be more cautious with the types of loans given, it would be expected that agricultural banks would be negatively affected and that even fewer agricultural loans would be originated. However, the strong commodity prices during the financial crisis may have led agricultural lenders to originate more agricultural loans.

The time period covered in the research covers three different economic time periods. The first time period to be evaluated is before the financial crisis. The second period is during the financial crisis, and the last period to be analyzed is after financial crisis. The three time periods will be compared to each other in order to determine if there are differences in banking efficiencies across the three periods and to determine if the financial crisis negatively affected the efficiency of banks in North Dakota.

Structure

This thesis is divided into five additional chapters. The following chapter discusses the relevant literature related to efficiency measurement, data envelopment analysis, and banking efficiency. Chapter three examines the methodology used for the motivation behind the estimation of the data and the model directly used in the efficiency estimation. Chapter four will discuss the data and its sources along with summary statistics of the data. Chapter five will examine and explain the results of the research, and chapter six will discuss the conclusions and implications this study has on the research and future studies.

CHAPTER 2: LITERATURE REVIEW

This chapter presents research related to productivity and efficiency measurement. The first section presents early studies that brought forth the idea of measuring efficiency. The following section discusses studies related to banking efficiency and history of efficiency measurement in banking. The third section discusses two of the most common methods for measuring efficiency: stochastic frontier analysis (SFA) and data envelopment analysis (DEA).

Measuring Efficiency

The origins of measuring efficiency can be traced to Farrell (1957). Farrell's goal was to develop an efficiency measure that could be used by economists. This would allow empirical testing of the measures and provide policy makers with a tool to determine the optimal level of output. Farrell developed a measure of efficiency that could account for multiple inputs and consisted of two components; technical and allocative efficiency. He proposed that technical efficiency shows the ability of a firm to obtain maximum output from a given set of input. The other component, allocative efficiency, is the ability of a firm to use the inputs in optimal proportions given their respective prices. The one problem with Farrell's efficiency measures was that they assumed the production function of an efficient firm was known which is rarely the case (Coelli 1995).

Building on the work of Farrell, Aigner and Chu (1968) developed a deterministic parametric approach that estimated a Cobb-Douglas production function and an efficiency frontier. However, this deterministic approach did not account for the possible influence of measurement errors and other noise on the shape of the frontier (Coelli 1995). The stochastic frontier approach (SFA) accounts for the possibility of measurement errors by using an error structure with a two-sided symmetric error term and one-sided error term (Aigner *et al.* 1977).

The two-sided symmetric error represents random fluctuations in costs and is usually assumed to be normally distributed while the one-sided error represents inefficiency and is assumed to be half-normally distributed. SFA allows for the estimation of standard errors and hypothesis testing. Yet, SFA had no a priori justification for the selection of any particular distribution of the error term (Coelli 1995). With the shortfalls of these models in measuring efficiency, came a need for a model that could measure the efficiency of a firm with no a priori information on the production function and weights of the inputs and output included in the model.

Charnes, Cooper, and Rhodes (1978) developed a model that addressed the issues that came with the SFA, and the use of data envelopment analysis began. They developed a method for measuring efficiency in decision making units (DMUs). The authors used engineering efficiency, the ratio of actual amount produced to the maximum amount that could be produced, as a platform for firm efficiency. They concluded that efficiency could be measured as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that similar ratios for every DMU be less than or equal to unity. This constraint means that the ratio cannot be greater than one, and the efficiency measures will be in the range from zero to one.

Charnes, Cooper, and Rhodes (1978) found the inefficiency measure by replacing the nonconvex and nonlinear formulations with linear programming. After finding the linear programming forms of efficiency, they developed data envelopment analysis by introducing subvectors of observed output and input values. These subvectors created an efficient frontier of the production possibilities curve. They concluded that no DMU could be rated efficient unless the intensity variable was equal to one and all the slack variables were zero. This rule was consistent with the conditions for Pareto efficiency.

The approach developed by Charnes, Cooper, and Rhodes became known as data envelopment analysis (DEA) and the CCR model. This nonparametric approach does not account for the possible influence of measurement error and other noise on the data like the parametric approach, but it does remove the need for the assumptions about the functional form of the frontier and distribution of the error term (Coelli 1995). It allowed for no a priori information on the weights of inputs used and outputs produced. It used actual data to construct a best practice frontier for the DMU under analysis and determined the marginal rate of transformation.

After the CCR model, DEA was applied to public school education to compare Program Follow Through and Non-Follow Through (Charnes *et al.* 1981). In this study, Charnes, Cooper, and Rhodes added to the original DEA model by developing programming that distinguished between management efficiency and program efficiency. DEA was again applied to education by evaluating the efficiency of occupational-technical programs (Bessent *et al.* 1983). Bessent et al. used extensions of DEA to evaluate new programs that may be used in combination with old programs at a community college. Banker, Charnes, and Cooper (1984) extended DEA to be used as a control tool for future planning purposes of firms. They separated technical and scale inefficiencies of the CCR model and then identified methods for correcting the inefficiencies. These works helped DEA become a common method for efficiency analysis in future research.

Applications of DEA

Since the popularization of data envelopment analysis, it has been applied to many industries to evaluate efficiency. Sharma, Leung, Zaleski (1999) used DEA to evaluate efficiencies in swine production in Hawaii. They used SFA and DEA to measure efficiencies and then compared the two approaches. The efficiencies were then regressed on farm specific factors in order to determine which factors affected swine production efficiency. The authors used input-reducing and cost-minimizing models for the DEA analysis and the Cobb-Douglas production function for the SFA analysis. Constant and variable returns to scale were assumed in each of the models used to evaluate the data.

They found through both approaches that there were significant inefficiencies in the production of swine in Hawaii. Through DEA, they were able to find that large farms operated with decreasing returns to scale and small and medium farms operated with increasing returns to scale. Output-based DEA models resulted in higher efficiencies than input-based DEA models, however this difference was not found to be significant. They also found that farm size, pigs produced, experience of producer, and feeding regime significantly affected efficiency levels.

Sharma, Leung, and Zaleski (1999) also discovered that technical and economic efficiencies were significantly higher for SFA models than DEA models when constant returns to scale were assumed; however, when variable returns to scale were assumed, the results between the two were very similar. Allocative efficiencies on the other hand were higher for DEA models. The differences between the two returns to scale assumptions revealed that the assumption made on a model is important to the analysis. The authors believed DEA models would be more sensitive to outliers and other noise; yet, they found the DEA results to be more robust than the SFA results. The authors were able to conclude that their results were consistent with the belief that SFA would yield higher efficiency scores than DEA.

Fraser and Cordina (1999) applied DEA to irrigated dairy farming systems in Northern Victoria, Australia. Dairy farmers were a major user of water in this area, and water use was a constraining input in their production. To ease the natural constraint that water put on production, dairy producers could purchase water on an annual basis for additional supply.

However, the supply of water available for purchase was capped. Due to this constraint, Fraser and Cordina studied the efficiency of dairy farms to see if water use could be reduced and constraints less restrictive to producers.

The authors relied on the base work of Farrell (1957) and Charnes, Cooper, and Rhodes (1978) to develop their DEA model. They used three DEA models to measure the efficiency of dairy farmers. The first model used was an input-orientated constant returns to scale model. The other two models were variable returns to scale models, and one was input-orientated while the other was output-orientated. By using one output and six inputs, Fraser and Cordina were able to calculate the efficiencies of 50 dairy farms.

They found more farms to be efficient under variable returns to scale because the constant returns to scale efficiency score was either less than or equal to the variable returns to scale efficiency score. They concluded that most farms were operating at near or full efficiency and that on average water use could be reduced by 16% to reach full efficiency. They found many farms to exhibit increasing returns to scale which meant that the farms should be larger than they were for their given factor mix.

Helmers and Shaik (1999) used three different DEA models to measure the efficiency of cropping systems. One model measures traditional efficiency and the other two models include a risk parameter. One of the risk-adjusted models treated risk as an undesirable output under weak disposability and the other as a normal input with strong disposability. The authors used an output reference set to measure an output distance function for two models and the third model calculates efficiency using an input distance function.

The authors found the risk-adjusted models led to higher efficiency measures for the group of cropping systems implying that risk is important to efficiency analysis. They were able to conclude that when risk is treated as an undesirable output higher efficiency scores were measured than when it was treated as a normal input. They were also able to find that the risk results paralleled net return analysis meaning that low net returns is related to low efficiency rankings and higher net returns are related to higher efficiencies.

Kapelko, Oude Lansink, and Stefanou (2012) applied DEA to the Spanish construction sector. They evaluated the dynamic efficiency of the sector pre- and post-financial crisis. The authors assumed a firm would minimize the discounted flow of costs over time subject to an adjustment-cost technology. They used a dynamic directional input distance function to determine the dynamic technical inefficiency. They concluded that firms could improve their technical performance by using a better management plan and that firms needed to be more flexible in adjusting the size of their operation.

Bank Efficiency

Banking efficiency was not as popular of an application of DEA after Charnes, Cooper, and Rhodes; however it became a more popular application in the late 1980s after the deregulation of the banking industry started. This deregulation increased the competition in banking, and in turn increased a need for measuring efficiency due to the increased competition. Technical efficiency measures were applied to banks by Rangan and Grabowski (1988). Using Farrell's efficiency measure as a guide, the authors decomposed overall technical efficiency of banks into pure technical efficiency and scale efficiency. Pure technical efficiency is the efficiency measure of the allocation of the resources of a DMU and is free of scale efficiencies. Scale efficiency measures whether the DMU is operating at the most efficient scale or size. The efficiency scores were then regressed against characteristics to determine what affects efficiency.

The authors used labor, capital, and purchased funds as inputs to produce outputs of real estate loans, commercial and industrial loans, consumer loans, demand deposits, and time and savings deposits. The banks in the study could reduce their inputs to produce the same amount of outputs, and banks were more scale efficient than pure technically efficient. Also, most of the technical efficiency was due to pure technical inefficiency or the inefficient allocation of resources. They concluded that efficiency was positively affected by bank size and negatively affected by product diversity.

Elyasiani and Mehdian (1990) used nonparametric DEA to derive efficiency measures and the rate of technological change of large U.S. commercial banks. Their research was also fueled by the added competitive environment and growth of technological change due to the deregulation of the banking industry. The authors used a nonparametric approach as it allowed for the disaggregation of inputs and outputs whereas parametric approaches aggregated inputs and outputs. They used an extension of Farrell's efficiency measure to find the proportionate reduction in input that can be achieved when a firm moves from its actual position to a point on its production frontier. They also wanted to measure the rate of technological change or the shift of the production frontier due to technological change between two years. They assumed that loans and investments were produced from deposits, labor, and capital. After constructing two production frontiers, banks were found to be able to produce the same level of output with less of the inputs they utilized, and there was technological progress between the two years studied.

Ellinger and Neff (1993) found that there were major issues when measuring bank efficiency. In particular, the authors found that there were differences in the sources of bank data and the definitions of bank costs and outputs. They also realized there were discrepancies in the empirical technique used, the functional form, the entity to evaluate, and the time period chosen.

They compared the definitions of outputs and inputs by using the value added and intermediation approaches. The intermediation approach regards loans and other assets as bank outputs while deposits and other liability funds as inputs, and the value added approach considers all assets and liabilities to have some output attributes and the determination of inputs and outputs is based on those variables that have the largest impact on the value added to the bank. They used a parametric and nonparametric technique to measure efficiency. The authors concluded that nonparametric models resulted in larger and more disperse measures of inefficiency as well as with using the intermediation approach.

Stochastic Frontier Analysis

Frontier efficiency analysis is the most common way to estimate bank cost inefficiencies and evaluate the effects of different changes to agricultural banks (Neff *et al.* 1994). The use of a profit frontier approach over a cost frontier approach includes bank output inefficiencies in the analysis and also puts less importance on bank input and output definitions. Using the Federal Reserve System Call Reports, Neff, Dixon, and Zhu (1994) evaluate cost inefficiencies and a profit frontier using stochastic frontier analysis. They imposed a functional form and two part error term on the model and used maximum likelihood and ordinary least squares (OLS) to measure the efficiencies and random shocks.

The authors found that inefficiency ratios were expressed as a percentage of total bank assets and lost return on assets (ROA) was due to inefficiencies (Neff *et al.* 1994). The cost frontier showed that ROA could be increased if all inefficiencies were eliminated. The profit frontier analysis resulted in higher estimates of inefficiency and showed that large levels of inefficiency exist and this contrasted with low levels from the cost approach. They were able to prove that the profit frontier addresses inefficiencies from bank outputs. Additionally, the profit frontier showed that inefficiency measures decreased with bank size. They concluded that the cost and profit frontier approaches resulted in very different estimates.

Scale and scope efficiencies are also measurable by conducting SFA. Scale efficiency determines whether a bank/firm is operating with the efficient level of outputs while scope efficiency measures whether a bank is operating with the efficient mix of inputs (Mester 1996). Mester measures whether a bank's observed cost will deviate from the cost frontier because of random noise and possible inefficiency. Using the intermediation approach to banking inputs and outputs, the author includes variables for financial capital and quality of loans into the SFA model. Quality is considered the average volume of nonperforming loans, and together with financial capital brings the risk preferences of the firm into the model.

After conducting a test for the functional form, Mester found that no scope economies or diseconomies exist in the banking data used and that no gains could be made by changing a bank's loan mix. She found that inefficient banks tend to be younger, have a higher percentage of loans in construction and land development, and more loans to individuals. The author concluded that the sample banks were operating at cost efficient output sizes and product mixes.

Armah and Park (1998) studied the efficiency of agricultural banks by also including risk in their study. They based their inclusion of risk into the study by realizing that many banking activities are influenced by each bank's management and their attitudes and behavior toward risk, and agricultural banks face three major sources of risk (Armah & Park 1998). Default risk occurs when borrowers cannot repay their loans and the accrued interest on the loans. Liquidity risk rises from the uncertainty about the bank's ability to maintain enough funds to meet customers' loan needs. Interest rate risk is the hazard of banks refinancing their long-term loans at interest rates above the current rates they receive.

Armah and Park (1998) showed that each manager has a utility function that is comprised of the risk-free rate of return, amount of nonperforming loans, the vector of output prices, and the level of financial capital. They also showed that managerial objectives can be tested using three criteria: evaluate the effects of the effective tax rate on a manager's choice of before-tax profit, assess the impact of the output price vector on a manager's cost minimizing plan, and evaluate the impact of non-interest income on the optimal demand for the inputs, profit, and financial capital.

Armah and Park (1998) used a stochastic efficient production frontier to measure the bank efficiency accounting for risk. They found that managers concerned with risk maximize their satisfaction by substituting high profits for reduced risk. They were able to conclude that models that ignore risk are not specified correctly and lead to incorrect conclusions about bank performance and support the need for risk inclusion in efficiency analysis.

Choi, Stefanou, and Stokes (2007) used stochastic frontier analysis to measure both technical and allocative cost inefficiencies in both a one- and two-step approach. The cost efficiency is a function of output produced, a vector of input prices, expenditures, and an error term. The one-step approach determines the cost frontier of the bank by including a pure random error and a one-sided error term in the model. The one-sided error term is a function of firm-specific characteristics. Maximum-likelihood estimation is then used to estimate the cost frontier. The two-step approach first calculates two efficiency scores, one for the beginning time period of the bank and one for the current time period. Finally, the cost efficiency score is calculated for the bank.

The authors categorized one single output as the sum of total loans and total deposits. The authors also categorize three inputs as labor, expenses for the premises and fixed assets, and other expenses. However, there was no explicit price information for the latter two of the three inputs. They found that the one-step approach produced a smaller cost efficiency measure than the two-step approach and that stochastic shocks contribute to inefficiency. They also concluded that ROA and cost efficiency exhibited a positive relationship through the two-step approach.

Data Envelopment Analysis

Yue (1992) evaluated the performance of Missouri banks in 1984 using DEA. The author explained the difference between microeconomic theory and DEA production frontiers. The technical and scale efficiencies of the commercial banks were evaluated. Yue (1992) used the intermediation approach in defining the inputs and outputs used in the DEA model. By applying the Charnes, Cooper, and Rhodes (CCR) model and additive DEA model, Yue explains what the overall efficiency measure consists of. The difference between the two models is that CCR model only allows for constant returns to scale and the additive model allows for variable returns to scale. The author was able to conclude that DEA is a highly flexible method in the measurement of bank efficiency.

Pastor (1999) measured DEA banking efficiency by including bad management risk and bad luck risk into his analysis. The bad management hypothesis states that risk arises from poor internal cost control and management not effectively screening loan applications while the bad luck hypothesis attributes risk to adverse economic circumstances (Pastor 1999). He found that deregulation in the European banking sector encouraged the Spanish banking system to take on riskier activities.

The author measured efficiency by jointly considering outputs, inputs, and environmental variables and restricting the optimization only to outputs and/or inputs in the analysis of a firm's performance. He directly included a risk variable into the DEA model and decomposed the variable into risk from poor management and risk from economic conditions. Additionally, the efficiency scores were regressed on bank characteristics to determine which may have an effect on efficiency. Pastor found a positive relationship between bank size and risk management efficiency. He concluded that risk management efficiency had a larger impact on overall efficiency than environmental efficiency and that risk management efficiency decreased with increased competition due to the deregulation of the industry.

Chang (1999) also measured banking efficiency by including risk in order to account for the quality of assets and loans and government regulations. He derived a risk-adjusted efficiency measure that took into account the costs associated with risk reduction, and this measure was able to determine the impact of financial regulations. He used the nonparametric approach as it allowed for multiple outputs, and the outputs could be distinguished between desirable and undesirable outputs. Using an extension of Farrell's technical efficiency measure, Chang imposed strong disposability assumptions on desirable outputs and weak disposability assumptions on undesirable outputs. He applied the model to rural banks in Taiwan, and used the intermediation approach to determine the inputs and outputs to the model.

He found risk-adjusted technical efficiencies to be slightly higher than efficiency measures not adjusted for risk. Higher efficiency scores resulted from the control of risky assets. He concluded that the proper treatment of nonperforming loans, an undesirable output, was very important to the model, and that efficiency comparison is hindered by ignoring risk.

Dias and Helmers compared agricultural and nonagricultural bank productivity using DEA (2001). A bank's total factor productivity growth is determined by measuring a Malmquist index. The Malmquist index is composed of technical change and efficiency change (Malmquist 1953). According to the authors technical change represent the shifting of the frontier to improvements in inputs and other technological changes while efficiency change represent the deviation from the frontier. The efficiency change measure accounts for bank differences in management.

By categorizing banks into different asset size groups and using the value-added approach of banking inputs and outputs, Dias and Helmers found differences in productivity gains between large agricultural banks and large nonagricultural banks. Agricultural banks experienced less technical change and innovations. The authors were able to conclude that efficiency gains could be realized by producing agricultural loans.

Choi, Stefanou, and Stokes (2007) also measured efficiency using data envelopment analysis using both a one- and two-step approach as previously described. They found that the one-step approach also produced a smaller cost efficiency measure with DEA. After conducting both SFA and DEA, they were able to conclude that bank-specific characteristics explain DEA efficiency scores better than SFA efficiency scores, and that most agricultural banks are either temporarily efficient or temporarily inefficient.

Settlage, Preckel, and Settlage (2009) developed an analysis and method of analyzing efficiency while including the risk averse behavior of a bank within a model. With the hypothesis of optimization, the authors develop a profit maximizing efficiency model that compares the observed profit level to the profit level that could be obtained if the bank were operating in an optimal manner.

The authors used the Federal Reserve System Call Reports for 2001 to develop a profit maximizing DEA model. After the authors determined the original profit maximizing model, they then added in a parameter that adjusted the model of risk calling this the risk-adjusted DEA model. The models required both quantities and prices for multiple inputs and outputs. The authors measured a cost minimizing efficiency score, a profit maximizing efficiency score, and a risk-adjusted profit maximizing efficiency score.

They found that both the cost minimizing and profit maximizing scores indicated low levels of efficiency for agricultural banks. On the other hand, the authors found that the risk-adjusted profit maximizing score showed higher levels of efficiency as risk averse behavior was accounted for. The authors were able to conclude that risk aversion and equity size were correlated and most banks were risk averse. They were able to find that efficient markets hypothesis is supported by risk-adjusted DEA, and traditional DEA may incorrectly characterize risk averse behavior as inefficiency.

The objective is to measure the efficiency of North Dakota banks before, during, and after the financial crisis. The efficiencies of agricultural banks will be compared to the efficiencies of non-agricultural banks to determine whether there is an efficiency difference between the two. Finally, the efficiency of different financial time periods will be compared in order to determine whether the financial crisis improved or declined banking efficiencies North Dakota.

CHAPTER 3: METHODOLOGY AND EMPIRICAL MODEL

Data Envelopment Analysis

Data envelopment analysis (DEA) is a nonparametric linear programming approach for measuring efficiency of decision making units (DMUs) by creating a frontier or envelope from input and output vectors. It produces individual measures of performance or efficiency. DEA allows multiple inputs and outputs to be considered for efficiency measurement without an assumption about the functional form of the frontier or distribution on the data (Coelli 1995). DEA efficiency measures can be computed without information about the input and output prices, and the measures can be decomposed into several components depending on the availability of the data. However, DEA does not account for the possible influence of measurement error or other noise on the data. It also does not allow for goodness of fit tests to be performed on the results, and large problems can be computationally intensive.

The measurement of efficiency is found by comparing observed and optimal levels of inputs and outputs. Efficiency measures can be decomposed into technical, allocative, and scale efficiency. Technical efficiency measures the ability of a DMU to produce as much output as input usage allows. Conversely, it could also measure the ability of a DMU to produce the same amount of output by using as little inputs as possible. Allocative efficiency measures the ability of a DMU to combine inputs and outputs in optimal proportions that satisfies the management objectives of the DMU. Additionally, it is considered as the ratio of the minimum cost at which a firm could secure its outputs to the cost of its technical efficient input levels for its input mix (Alsarhan 2009). Scale efficiency measures the optimal production volume level of the DMU. It is also considered a measure of a DMU's productivity at a given level with respect to what it could produce if it produced at the most productive size (Alsarhan 2009).

Economic Theory

The economic theory of efficiency implies that the value of output is expected to exceed the value of inputs due to the "value added" in production (Yue 1992). A single DMU is considered technically efficient if it cannot increase output or reduce an input without reducing other outputs or increasing other inputs. Economic efficiency occurs when a firm finds the combination of inputs that allows them to produce the desired level of output at the minimum cost (Yue 1992).

Technical efficiency can be explained by using a simple example. Assume that a firm uses two inputs, x_1 and x_2, to produce one output, y. Therefore, the production function can be represented as:

$$y = f(x_1, x_2). \tag{1}$$

This production function is assumed to be subject to constant returns to scale. In Figure 3.1, let the area above and to the right of y_0 represent all of the combinations of inputs that can produce at least the given output of y_0. Line *PP* represents the prices of inputs and is called the isocost line. Since efficiency occurs at the point of cost minimization, efficient operation occurs at point *C*. If point *D* represents the output produced by a particular firm, then overall efficiency (OE) is measured as the ratio of *OA/OD*. This ratio represents optimal input usage to actual input usage.

Overall efficiency can then be decomposed into technical and allocative efficiency. A firm is technically efficient if it is operating on the isoquant, y_0, and this makes point *D* technically inefficient. The technical efficiency (T) can be measured by the ratio of *OB/OD*, and allocative efficiency (A) is measured by the ratio *OA/OB*. Since overall efficiency is composed of technical and allocative efficiency, the relationship between the three can be represented as:

$$OE = T * A. \tag{2}$$

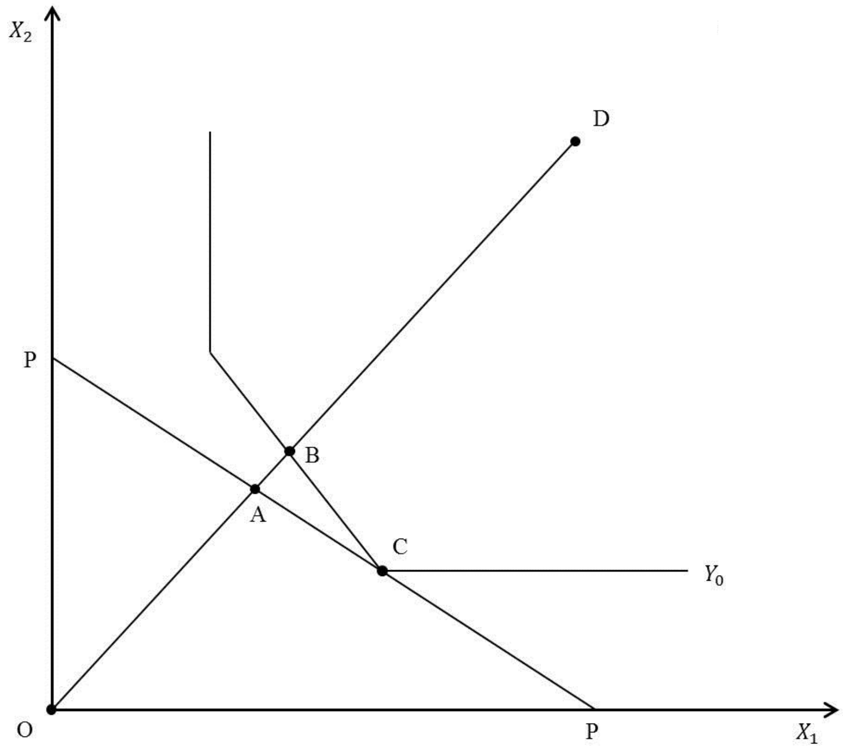


Figure 3.1 – Overall, Technical, and Allocative Efficiencies

Primal Production DEA

A production process transforms inputs into outputs. Primal production theory suggests that the relationship between output quantities and input quantities can be examined. A production function is used to represent this relationship by constructing a production possibilities set as seen in Figure 3.2. The production possibility set is the output mix produced from the inputs. The production possibility set is made up of the feasible input and output combinations that come from available production technology. The relationship between the two can take on different relationships. For example, one input can produce one output, one input can produce many outputs, multiple inputs can produce one output, or multiple inputs can produce multiple inputs. The theoretical production possibility set is the maximum amount of output that can be produced from an input level, and it is the minimum input required to obtain a desired output level.

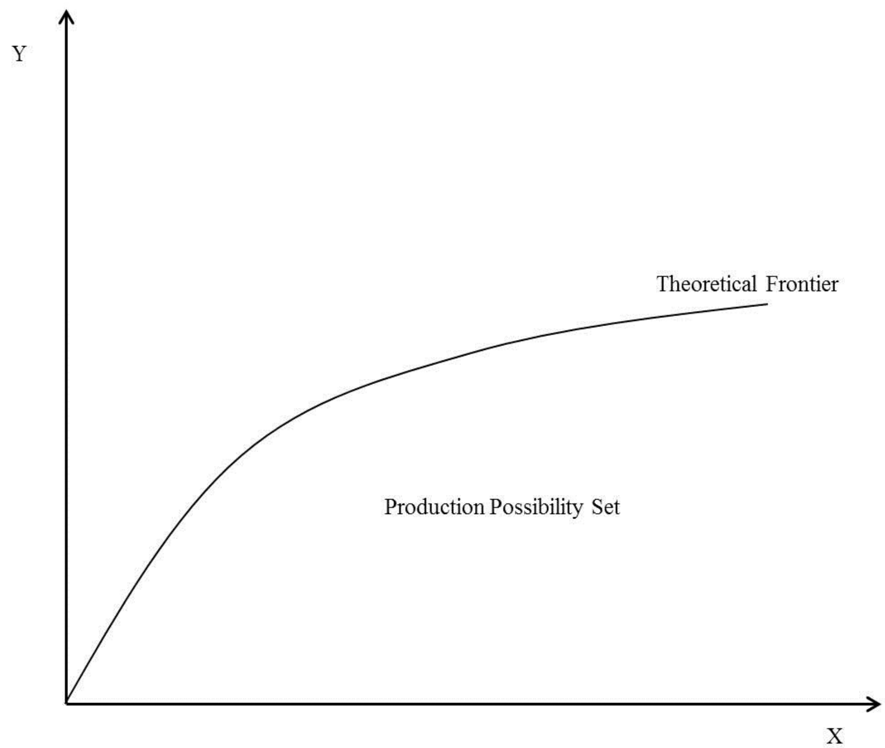


Figure 3.2 – Production Possibility Set

Only observed data can identify the empirical production frontier which is usually below the theoretical frontier as shown in Figure 3.3. The empirical production function or efficiency frontier is the best practice envelopment surface. The efficiency frontier establishes a benchmark efficiency score of unity that no individual DMU's score can exceed. Total efficiency is the distance from an observed DMU to the theoretical frontier while relative efficiency is the distance from the same point to the efficient frontier. The DMUs that form the efficient reference set make up the peer group. DEA takes the observed input and output quantities to form a production possibility space which the DMUs are compared to determine their technical efficiency.

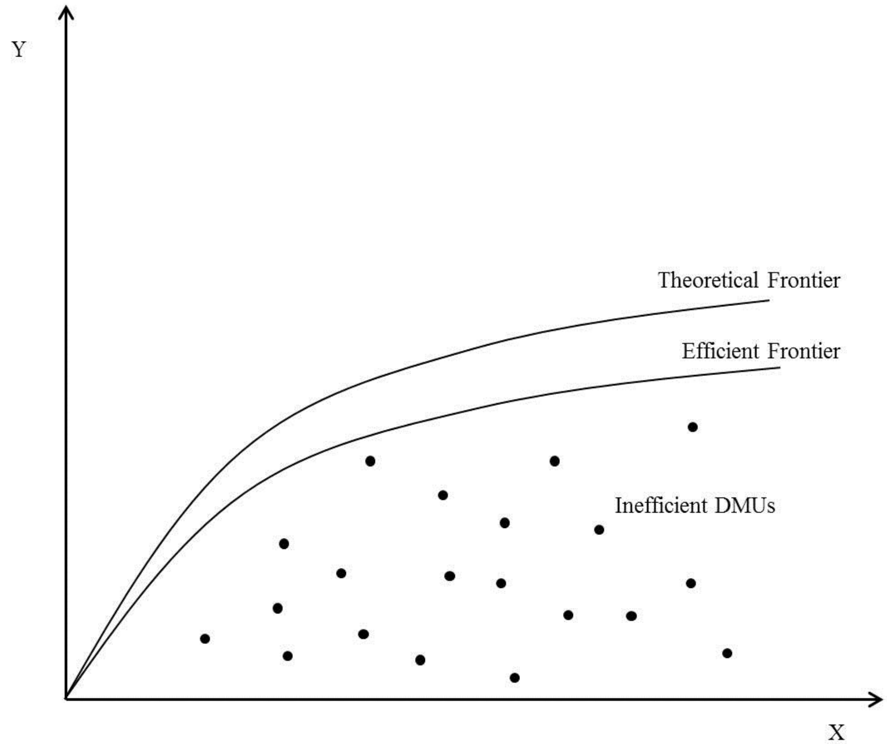


Figure 3.3 - Frontiers

DEA can be input or output oriented. The firm may try to maximize the outputs produced given the set of inputs, or it may try to produce the same amount of output by reducing the inputs. An input-orientated DEA model minimizes the inputs used to produce a desired output level while an output-orientated model maximizes output from the given inputs. A third model can be obtained as a collection of all inputs and outputs that are technically feasible. DEA efficiency is consistent with Pareto optimality in economic theory (Sherman & Gold 1985). Pareto optimality states that a DMU is not efficient if it is possible to increase an output without increasing any of the inputs and without lowering any other output and vice versa (Avkiran 2011).

Output and input sets can be represented by output or input distance functions for k DMUs where k represents DMUs from 1 to K. A distance function is a comparison of the observed quantities over the realized or optimal quantities. In Figure 3.4, the input distance function is the maximum feasible decrease of input for a given amount of output and is represented by:

$$D_i(x^k, y^k)^{-1} = \min_{\lambda,z} \lambda \qquad (3)$$

subject to: $y_j^k \leq zY \qquad j = 1, 2, \ldots, M$

$\lambda x_i^k \geq zX \qquad i = 1, 2, \ldots, N$

$z \geq 0,$

where *I* denotes the function to be input-oriented, *k* represents DMUs from 1 to *K*, *Y* is the vector of output for *K* DMUs, *X* is the vector of inputs for *K* DMUs, *j* represents the number of outputs for the k^{th} DMU from 1 to *M*, and *i* is the number of inputs for the k^{th} DMU from 1 to *N*. The distance of a point from the efficient frontier is represented by λ at which the DMU wants to minimize in order to be more efficient. The intensity variables, *z*, represent the weights given to the vectors of output and inputs.

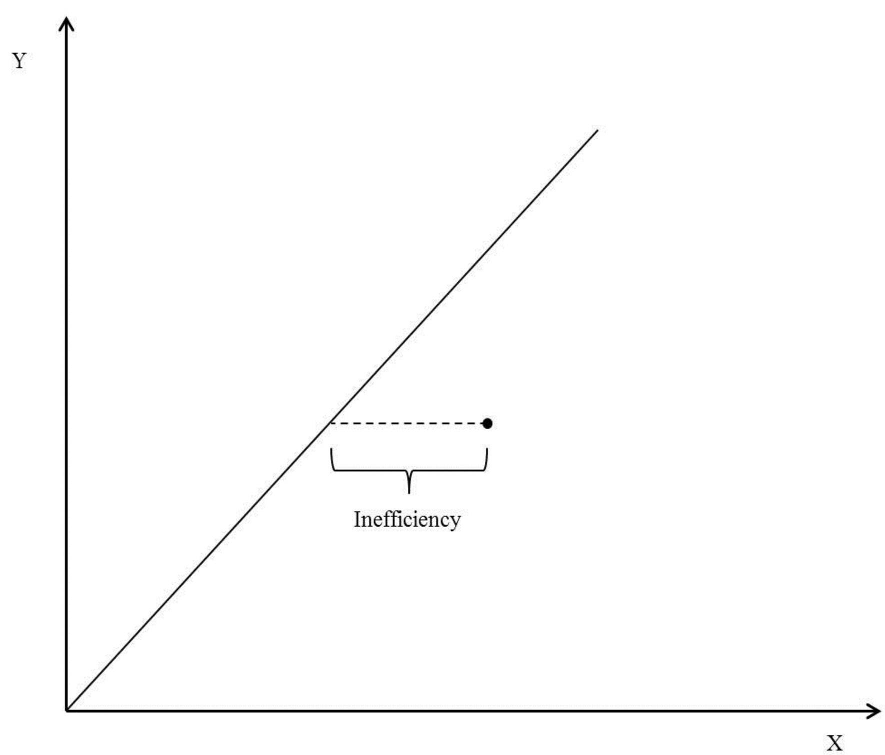


Figure 3.4 – Input Distance Function

The output distance function, in Figure 3.5, is the maximum feasible increase of output given input and is defined as:

$$D_0(x^k, y^k)^{-1} = \max_{\theta,z} \theta \tag{4}$$

subject to: $\theta y_j^k \leq zY \qquad j = 1, 2, \dots, M$

$zX \leq x_i^k \qquad i = 1, 2, \dots, N$

$z \geq 0,$

where *O* denotes the function to be output-oriented, *k* represents DMUs from 1 to *K*, *Y* is the vector of output for *K* DMUs, *X* is the vector of inputs for *K* DMUs, *j* represents the number of outputs for the k^{th} DMU from 1 to *M*, and *i* is the number of inpust for the k^{th} DMU from 1 to *N*. The distance of a point from the efficient frontier is represented by θ and is minimized by a DMU in order to reach efficiency. The intensity variables, *z*, represent the weights given to the vectors of output and inputs.

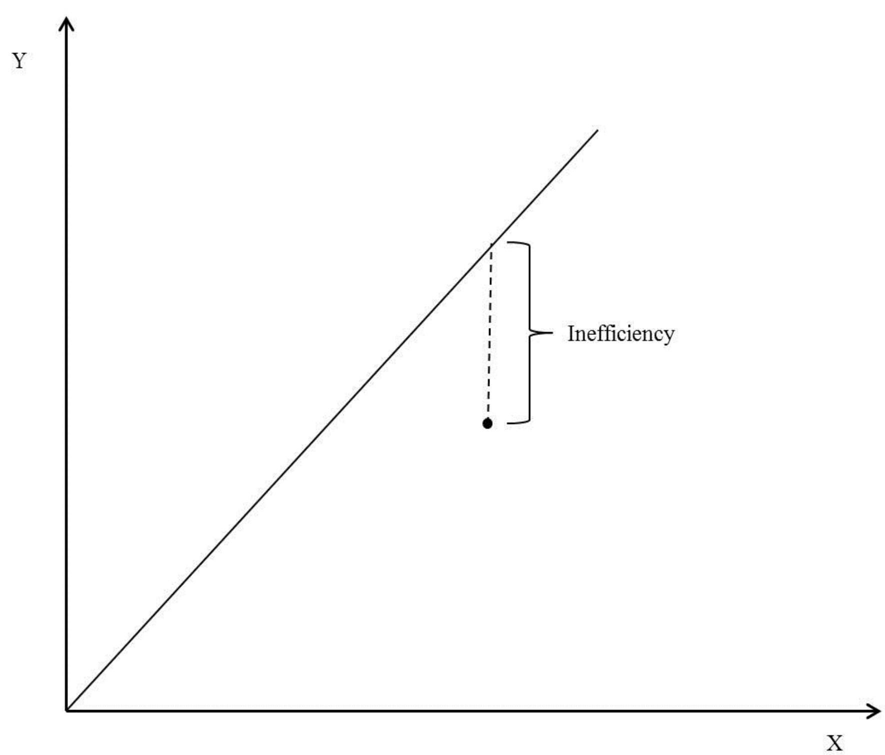


Figure 3.5 – Output Distance Function

CCR Model

The Charnes, Cooper, and Rhodes (CCR) model generalized Farrell's single output to multiple input ratio to multiple outputs and inputs. The CCR model for efficiency shows that efficiency scores for DMUs are a function of the weights of inputs and outputs combinations, and one of the main constraints for the model is that the weights have to be less than or equal to unity. The CCR model also assumes constant returns to scale.

A ray out of the origin that is tangent to the production function marks the point of efficiency. The model finds technical, scale, allocative, and economic efficiencies. Technical efficiency under constant returns to scale is referred to as overall technical efficiency. Overall technical efficiency can be decomposed into pure technical inefficiency and scale inefficiency. Pure technical efficiency is the efficiency measure of the allocation of the resources of a DMU. Scale efficiency measures whether the DMU is operating at the most efficient scale or size. The economic efficiency is found from the cost-minimizing DEA model. Overall economic efficiency is the ratio of the minimum cost to the observed cost.

The CCR primal input oriented model is:

maximize $h_0 = \sum u_r y_{r0}$ (5)

subject to: $\sum u_r y_{rj} - \sum v_i x_{ij} \leq 0 \quad j = 1,2, \ldots, n$

$\sum v_i x_{i0} = 1$

$u_r \geq 0 \quad r = 1,2, \ldots, s$

$v_i \geq 0 \quad i = 1,2, \ldots, m,$

where h_o is the output level of the DMU being analyzed, y_{r0} is the output for DMU being analyzed, x_{i0} is the input for the DMU in question, and y_{rj} represents the output for the j^{th}

DMU while x_{ij} is the input for the j^{th} DMU. The weight associated with the outputs and inputs are u_r and v_i respectively.

The CCR primal input oriented model maximizes the ratio of output to input which is equal to the ratio of the weighted outputs to the weighted inputs. The weights, u_r and v_i, would be equivalent to prices that are used in economic production theory. However, the CCR model is only concerned with quantities in primal production, and therefore they are considered weights. This ratio of weighted outputs to the weighted inputs is the distance from the output being considered to the efficient frontier and is the efficiency measure.

The level of inefficiency is defined as the proportional reduction in input quantities that can occur while maintaining the level of output. This is the proportionate reduction in input that can be achieved when the firm moves from its actual position to a point on its production frontier.

Returns to Scale

One can place an assumption on a DEA problem based on the returns to scale of production for the DMU's under consideration. There are two types of returns to scale which refer to the slope of the frontier: constant returns to scale (CRS) and variable returns to scale (VRS). Constant returns to scale occurs when proportional increases in inputs result in proportional increases in outputs while variable returns to scale does not result in proportional increases in inputs and outputs.

Under variable returns to scale the sum of the intensity variable used in the model equal one and form convex combinations (Färe *et al.* 1990). A model that exhibits variable returns to scale has portions of the production frontier that exhibit increasing, decreasing, and constant returns to scale each. In Figure 3.6, segment *AB* exhibits increasing returns to scale while segment *CD* shows decreasing returns to scale. The segment *BC* exhibits constant returns to scale. The technology exhibited in segment *OF* represents a model that is subject to constant returns to scale.

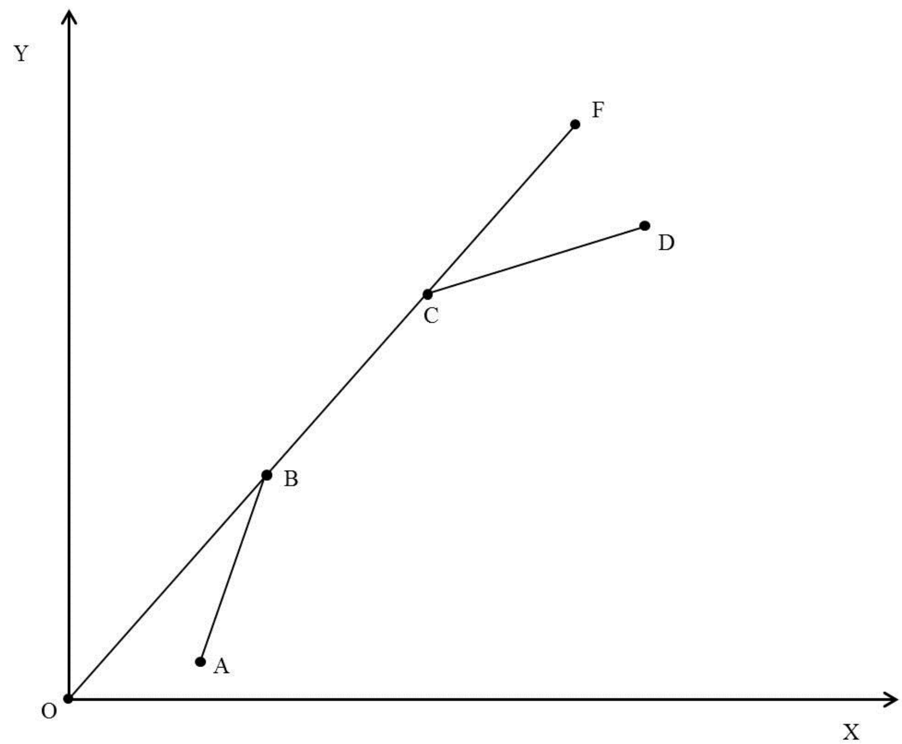


Figure 3.6 – Returns to Scale

BCC Model

The Banker, Cooper, and Charnes (BCC) model measures pure technical efficiency which is the efficiency that comes from the allocation of the resources for a DMU. It adds onto the CCR model by including a constraint that allows for variable returns to scale.

The BCC primal model is defined as:

$$\text{minimize}_{\lambda}\, z_0 = \theta_0 \qquad (6)$$

subject to: $\sum \lambda_j\, y_{rj} \geq y_{r0} \qquad r = 1, 2, \dots, s$

$\theta_0 x_{i0} - \sum \lambda_j\, x_{ij} \geq 0 \quad i = 1, 2, \dots, m$

$\sum \lambda_j = 1;\ \lambda_j \geq 0 \qquad j = 1, 2, \dots, n,$

where θ_0 is the input distance between the observed output of the DMU and the optimal output on the efficient frontier, y_{r0} is the output for the DMU being analyzed, x_{i0} is the input for the DMU in question, and y_{rj} represents the r^{th} output for the j^{th} DMU while x_{ij} is the i^{th} input for the j^{th} DMU. The weights associated with the outputs and inputs are λ_j. The weights, λ_j, have to be greater than zero, and the sum of them have to equal one which allows for variable returns to scale.

Assuming that a DMU uses one input to produce one output, the BCC efficiency model minimizes the inefficiency or the input distance between the observed output and the optimal output. This is can be seen in Figure 3.7. θ represents the inefficiency of the DMU being analyzed and is equivalent to one minus the efficiency.

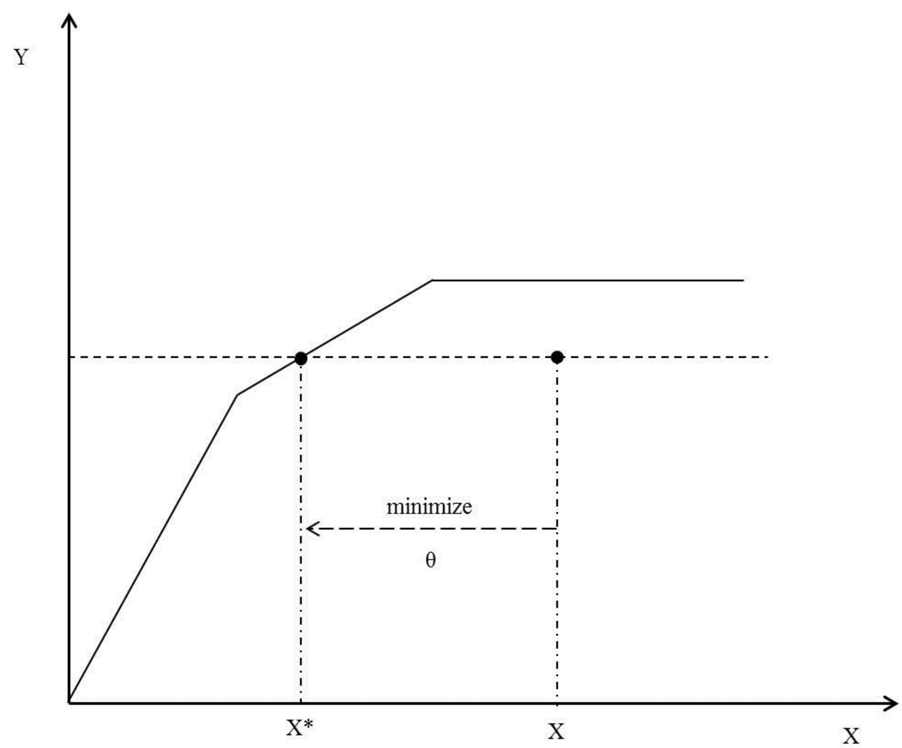


Figure 3.7 – BCC Model

Empirical Model

Following the BCC model, an input-oriented model is used for measuring the efficiency of banks in the study. As stated earlier, the BCC model includes a constraint that allows for variable returns to scale in production, and it minimizes the input distance from the observed output to the optimal output. The model used for the analysis can be defined as:

$$\text{minimize}_{\lambda}\, z_0 = \theta_0 \tag{7}$$

subject to: $\sum \lambda_j\, y_{rj} \geq y_{r0} \qquad r = 1, 2, \dots, s$

$$\theta_0 x_{i0} - \sum \lambda_j\, x_{ij} \geq 0 \quad i = 1, 2, \dots, m$$

$$\sum \lambda_j = 1;\ \lambda_j \geq 0 \qquad j = 1, 2, \dots, n,$$

where θ_0 is the input distance between the observed output of the DMU and the optimal output on the efficient frontier, y_{r0} is the output for the DMU being analyzed, x_{i0} is the input for the DMU in question, and y_{rj} represents the r^{th} output for the j^{th} DMU while x_{ij} is the i^{th} input for the j^{th} DMU. The weights associated with the outputs and inputs are λ_j. The weights, λ_j, have to be greater than zero, and the sum of them have to equal one which allows for variable returns to scale.

The model evaluates the efficiency of North Dakota banks by using three inputs to produce two outputs. Inputs and outputs are chosen for the model by using the intermediation approach to banking instead of the value added approach. The intermediation approach views banks as providing intermediary services between depositors and borrowers (Ellinger & Neff 1993). This means that banks use their liabilities to produce assets. The simplest view of the intermediation approach to banking assumes that banks use deposits from customers to produce loans to other customers. The value-added approach assumes that all assets and liabilities may have some output attributes where the determination of outputs is based on those that have the largest impact on value added (Ellinger & Neff 1993).

For the model to be consistent with the basic view of the intermediation approach, total deposits were included as an input and net loans and leases as an output. Capital and labor are considered to be inputs and were proxied by premises, fixed assets, and capital leases and employees respectively as the other two inputs. Investment securities were chosen as an output as it is an asset on a bank's balance sheet, and because all banks in the analysis consistently produced investment securities. Other variables were not included in the model in order to maintain the robustness of the results, and to avoid problems of one variable masking the other variables.

Table 3.1 – Input Variables

Name	*Measurement*
x_1 = Total Deposits	Thousands of Dollars
x_2 = Premises, Fixed Assets, & Capital Leases	Thousands of Dollars
x_3 = Employees	Units (full-time equivalents)

Table 3.2 – Output Variables

Name	*Measurement*
y_1 = Net Loans & Leases	Thousands of Dollars
y_2 = Investment Securities	Thousands of Dollars

CHAPTER 4: DATA

This chapter describes the data sources and the conditions required for the model. In formulation of the datasets, one main data source is used with a secondary data source for missing values.

Quarterly Bank Reports

Data on the banking institution level quarterly financial statements from fourth quarter 2002 (Q4:2002) to fourth quarter 2012 (Q4:2012) are derived from the Uniform Banking Performance Reports (UBPR) which are published by the Federal Financial Institutions Examination Council (FFIEC). This data is publicly available through the FFIEC or the FDIC.

Using the FDIC's bank find tools, a list of banking institutions with branches operational in the state of North Dakota was compiled. This list resulted in 99 active banks. Two banks were eliminated from the data as they were savings and thrifts banks and a UBPR was not available for them. Three additional banks were also removed from the dataset as they were not active during the entire time period being evaluated. These banks either began operation during the period of time being researched, or they became inactive through failure or a bank merger. The final dataset consists of 94 banks with 41 quarters.

The variables were obtained from the banks' balance sheets. All of the variables included in the model were available from the UBPRs with the exception of the number of full-time employees for a bank. The full-time employee variable was extracted from the FDIC's summary banking information on each individual bank.

Bank Classifications

Banks were first divided by the classification of agricultural or non-agricultural. This division was decided by the FDIC's definition of an agricultural bank. These are banks with agricultural production loans plus real estate loans secured by farmland in excess of 25% of the bank's total loans and leases. This classification created a set of 69 agricultural banks and 25 non-agricultural banks.

Agricultural and non-agricultural banks were then divided into three different classifications each based on the asset sizes of the banks to account for any bias that may occur with comparing large banks to small banks. The three asset sizes for agricultural banks are banks with assets less than $50 million (small), banks with assets between $50 million and $100 million (medium), and banks with assets greater than $100 million (large). Non-agricultural banks were divided into one of the following three classifications: banks with assets less than $500 million (small), banks with assets between $500 million and $1 billion (medium), and banks with assets greater than $1 billion (large).

Table 4.1 – Bank Classifications

Type of Bank	***Number of Banks***
Small Ag: Assets < $50 Million	32
Medium Ag: Assets between $50 and $100 Million	21
Large Ag: Assets > $100 Million	16
Total Agricultural Banks	*69*
Small Non-Ag: Assets < $500 Million	12
Medium Non-Ag: Assets between $500 Million and $1 Billion	7
Large Non-Ag: Assets > $1 Billion	6
Total Non-Agricultural Banks	*25*
Total Banks	**94**

Additionally, the dataset was divided into three time periods to represent pre-financial crisis, the financial crisis, and post-financial crisis. The pre-financial crisis period consisted of Q4:2002 through Q4:2007. The time period denoted by Q1:2008 to Q4:2009 represented the financial crisis, and finally Q1:2010 through Q4:2012 was the post-financial crisis period.

Summary Statistics

The most commonly used statistic to describe banks is asset size. The average asset size of the 94 banks included in the study is $9.98 billion with a range from $14.98 million to $618 billion in assets. The agricultural banks had an average asset size of $107.3 million compared to the average of $37.2 billion in assets for non-agricultural banks. The distribution for bank sizes is presented in Figure 5.1.

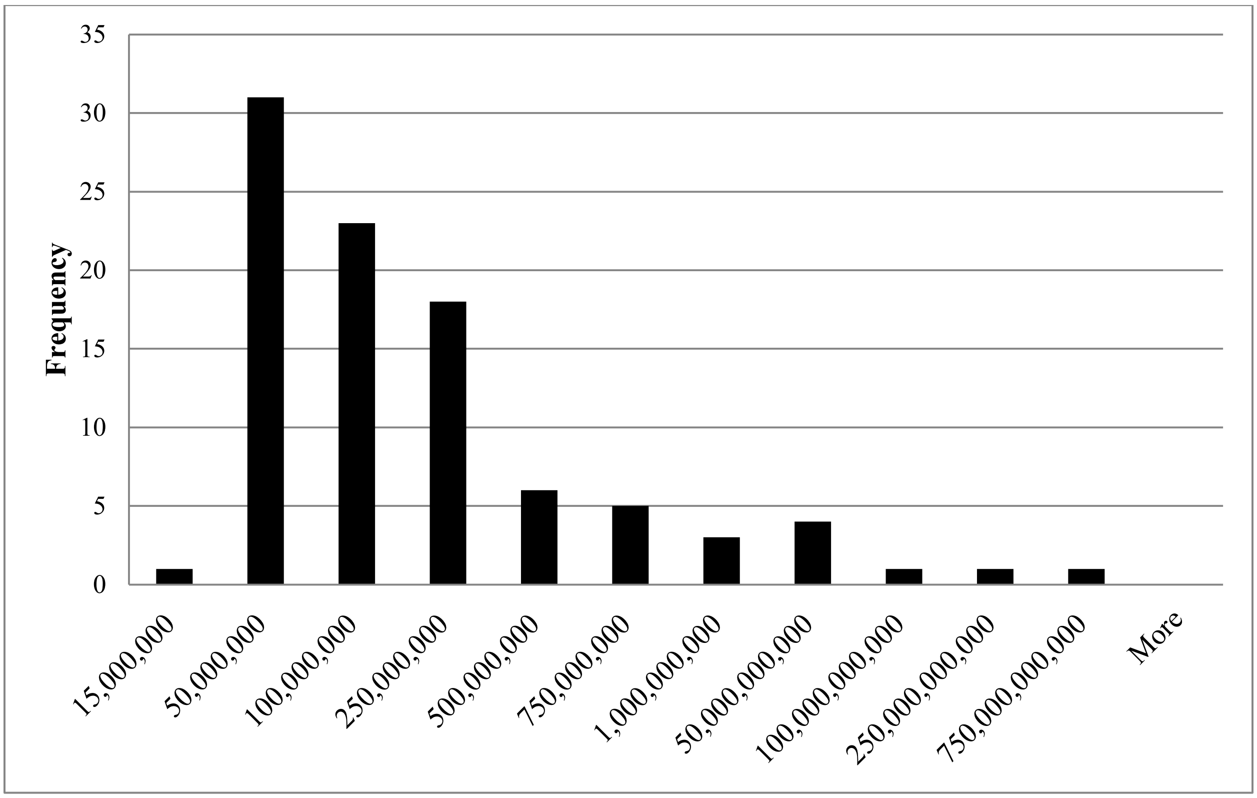


Figure 4.1 – Asset Distribution

Deposits grew throughout out the time period for all banks on average as total deposits in thousands before the financial crisis was $4,578,596, during the crisis was $6,501,752, and after the financial crisis was $12,420,773. Non-agricultural banks had significantly more deposits during the entire time period with $26,947,028 thousand compared with $102,440 thousand for agricultural banks.

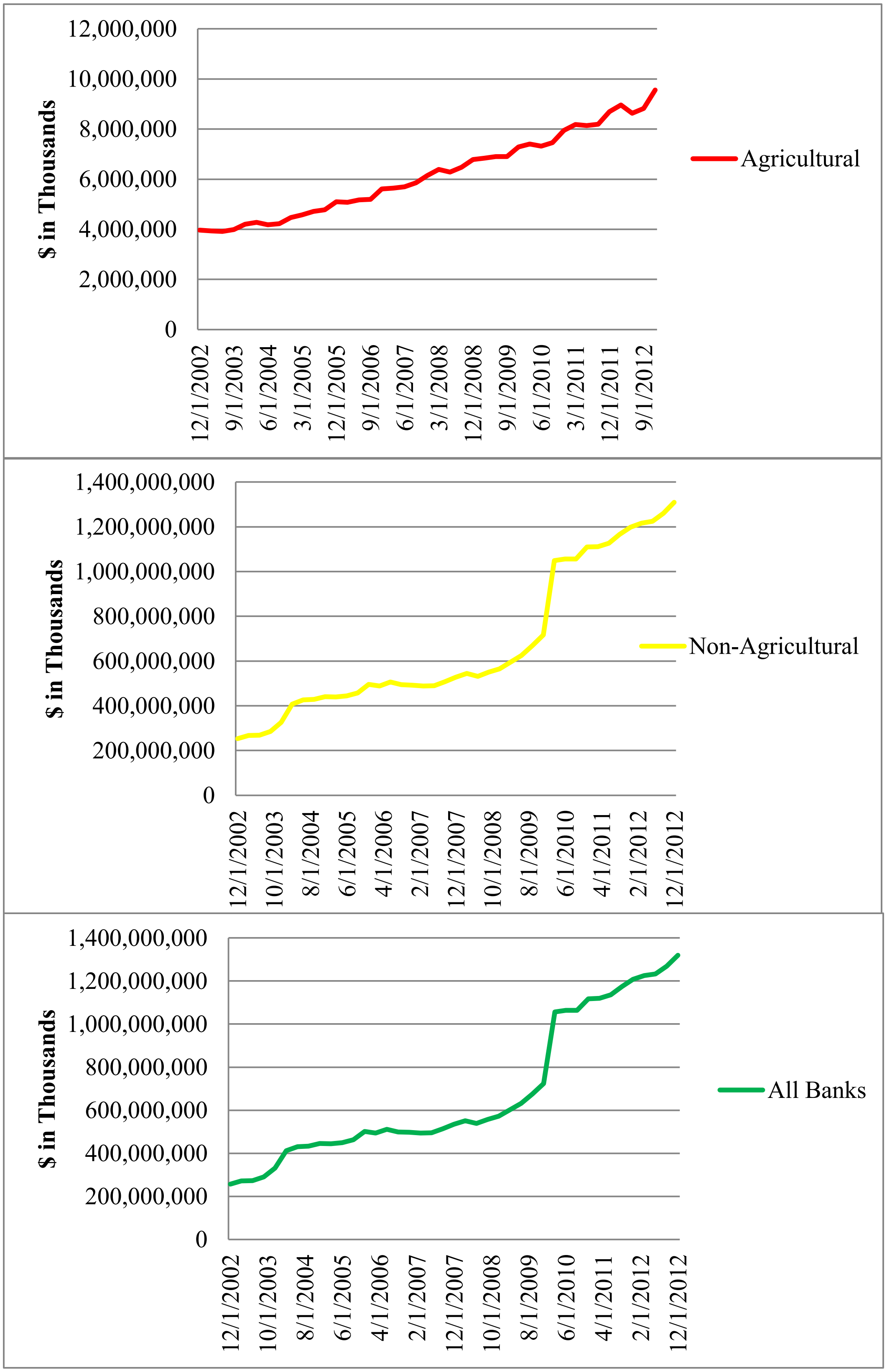


Figure 4.2 – Total Deposits by All Banks, Ag Banks, and Non-Ag Banks

Over the ten year period being analyzed, banks increased their premises, fixed assets, and capital leases. Before the financial crisis, all banks had an average of $60,650 thousand of this variable. All banks increased this variable during and after the financial crisis with an average of $75,411 thousand and $120,609 thousand respectively. Non-agricultural banks had a greater amount of premises, fixed assets, and capital for the entire period compared to agricultural banks. For the decade, non-agricultural had an average of $299,434 thousand and agricultural banks had an average of $2,021 thousand.

Table 4.2 – Means of Premises, Fixed Assets, and Capital Leases

Type of Bank	*All Periods*	*Pre-Crisis*	*Crisis*	*Post-Crisis*
All Banks	$80,900.11	$60,649.71	$75,411.07	$120,609.12
Agricultural	2,021.33	1,373.69	2,012.08	2,150.43
Non-Agricultural	299,433.87	224,251.50	275,790.31	446,765.39
Small Ag	424.83	361.57	458.13	512.55
Medium Ag	774.79	699.18	813.63	881.24
Large Ag	7,144.01	4,283.25	6,525.31	7,144.01
Small Non-Ag	3,786.91	2,879.25	3,262.21	5,114.83
Medium Non-Ag	15,006.82	11,783.67	15,894.48	20,055.54
Large Non-Ag	1,222,559.53	914,875.12	1,122,227.46	1,827,894.67

The average number of employees for all banks during the entire period was 2,264. Most types of banks increased their number of employees across the time being evaluated with the exception with of small agricultural banks and small non-agricultural banks. Small agricultural banks kept the same number of banks on average before and during the financial crisis with an average of 11 employees during each period. After the financial crisis, small agricultural banks decreased the number of employees to 10. Small non-agricultural banks decreased the number of employees from before the crisis to during the crisis and then increased employees after the financial crisis. Small non-agricultural banks had on average 57, 52, and 110 employees before, during, and after the financial crisis respectively.

Table 4.3 – Mean of Employees

Type of Bank	*All Periods*	*Pre-Crisis*	*Crisis*	*Post-Crisis*
All Banks	$2,264.11	$1,766.56	$2,260.76	$3,156.58
Agricultural	34.11	27.86	32.96	33.50
Non-Agricultural	8,431.26	6,565.49	8,342.63	11,755.46
Small Ag	10.68	10.74	10.65	10.47
Medium Ag	19.49	18.78	19.59	20.65
Large Ag	97.08	74.00	92.82	97.08
Small Non-Ag	75.85	57.07	51.69	109.57
Medium Non-Ag	304.95	265.31	297.80	379.08
Large Non-Ag	34,622.78	26,932.52	34,264.38	48,319.67

Even with banks being more selective in their loan selection process during and after the financial crisis, loans and leases originated increased throughout the time period. The average net loans and leases for all banks were $4,530,108 thousand, $6,235,172 thousand, and $10,438,881 thousand before, during, and after the financial crisis respectively. Non-agricultural banks on average originate more loans and leases than agricultural banks with each producing $24,525,845 thousand and $85,796 thousand respectively.

Table 4.4 – Means of Net Loan and Leases

Type of Bank	*All Periods*	*Pre-Crisis*	*Crisis*	*Post-Crisis*
All Banks	$6,577,155.38	$4,530,107.85	$6,235,171.51	$10,438,881.43
Agricultural	85,795.57	58,610.76	84,822.50	94,213.45
Non-Agricultural	24,525,844.83	16,871,439.83	23,025,624.32	38,921,200.59
Small Ag	21,044.22	18,205.57	21,719.92	25,218.32
Medium Ag	40,722.77	33,565.97	43,215.21	51,585.52
Large Ag	290,194.34	172,292.40	258,972.22	290,194.34
Small Non-Ag	140,133.01	103,823.54	158,900.17	191,163.13
Medium Non-Ag	447,274.05	351,938.05	496,618.23	581,215.93
Large Non-Ag	101,388,934.40	69,679,424.49	95,042,913.06	161,111,257.63

Banks continued to create investment securities throughout and after the financial crisis even with the economic recession and concern with banking and investments. Average investment for all banks increased across the periods with $858,876 thousand before the financial crisis, $1,432,125 thousand during the crisis, and $2,622,761 thousand after the financial crisis.

Non-agricultural banks created significantly more investment securities than agricultural banks. The two types of banks created $5,520,878 thousand and $22,258 thousand respectively. All summary statistics including standard deviations for all variables included in the model can be found in Appendix A.

Table 4.5 – Means of Investment Securities

Type of Bank	*All Periods*	*Pre-Crisis*	*Crisis*	*Post-Crisis*
All Banks	$1,483,404.46	$858,875.89	$1,432,124.83	$2,622,760.62
Agricultural	22,257.79	16,684.16	20,391.26	27,610.06
Non-Agricultural	5,520,877.76	3,183,325.07	5,286,157.48	9,768,075.15
Small Ag	9,519.25	8,892.30	9,384.94	10,833.26
Medium Ag	17,817.51	14,460.10	17,943.12	23,609.22
Large Ag	66,823.23	35,186.94	44,551.68	66,823.23
Small Non-Ag	51,591.68	34,363.76	54,074.56	82,970.39
Medium Non-Ag	154,795.52	117,408.46	121,640.18	242,326.45
Large Non-Ag	22,719,879.20	13,058,150.42	21,784,248.83	40,251,658.14

CHAPTER 5: RESULTS AND IMPLICATIONS

Data envelopment analysis is applied to measure the efficiency of 94 banks using a panel dataset from Q4:2002 to Q4:2012 creating 3854 observations. A summary of the efficiency scores calculated is presented in Table 5.1. Mean efficiencies are presented for each different time period as well as for each classification of bank. This allows for comparisons to be made between time periods and banks. A means-variance test was then performed on the results to determine if there were significant differences among the efficiency results. A full summary of the results and means-variance test can be found in Appendix B.

Based on the results in Table 5.1, the average efficiency of all banks during all time periods is 0.83. They show that both agricultural and non-agricultural banks exhibit inefficiencies in their production processes with non-agricultural banks being slightly more efficient than agricultural banks. When all periods are considered together, agricultural banks have a mean efficiency score of 0.82 and non-agricultural banks have a score of 0.86. The results also show efficiency scores to increase slightly from period to period. Agricultural banks have scores of 0.80, 0.83, and 0.86 before, during, and after the financial crisis respectively. Non-agricultural banks have scores of 0.84, 0.86, and 0.89 for the time periods before, during, and after the crisis respectively.

These results present interesting conclusions that would afford more analysis. It shows that agricultural banks in North Dakota are less efficient than non-agricultural banks. This is surprising as agriculture has been the leading industry in North Dakota until the energy sector became the leader in 2012. As regression analysis was not performed, it is hard to determine if agricultural lending leads to lower efficiency while commercial and other types of lending leads to higher scores.

It is also interesting that efficiency results increased across the analyzed periods and that efficiency scores were not the lowest during the financial crisis as would have been assumed. This result is interesting in a time period when many banks were having insolvency issues and were failing. Non-agricultural and agricultural banks in North Dakota were able to perform well during the financial crisis as compared to before. This could have been because of new banking restrictions put in place by the federal government during the crisis and supplying the banking industry with more funds in order to perform their activities.

The means-variance test was able to support the evidence found by the results. There was a significant difference between the efficiency scores of the different types of banks being evaluated at the 1% significance level. The test also showed a significant difference between the three time periods being evaluated with the efficiency increasing over time meaning that the post-crisis period was the most efficient and the pre-crisis period was the least efficient. Interestingly, as the mean efficiency increased over time, the variance in the efficiency scores also increased over time. This means that even though the mean efficiency increased, the variation in the scores among the banks in the specific time period varied more. However, when the interaction between the type of bank and time period being analyzed was taken into account the differences in efficiency were less significant. The interaction between the type of bank and time period was significant at 17.6 %. The results are more reliable when comparing just bank types against each other or comparing time periods. Nonetheless, the results still offer interesting findings across all time periods and all bank types.

Among agricultural banks, the results show that large agricultural banks are the most efficient across all time periods followed by small agricultural and medium sized agricultural banks being the least efficient of the agricultural banks. The large agricultural banks have scores of 0.81, 0.85, and 0.87 before, during, and after the financial crisis respectively. Small agricultural banks reveal scores of 0.80, 0.83, and 0.86 for the same time periods while medium agricultural banks have scores of 0.78, 0.82, and 0.85.

These findings are surprising because they show that banking efficiency among agricultural banks does not increase with size as the medium size banks are the most inefficient of the agricultural banks. However, one can still confirm that when an agricultural bank operates with more than $100 million in assets, it becomes more efficient. The agricultural banking results also show that efficiency of banks increased over time, and that efficiency was not impacted during the financial crisis. This helps support the idea that high commodity prices at the beginning of the financial crisis were sufficient and able to help agricultural banks perform at higher levels than before the crisis. As stated before, the commodity prices did not fall below the price levels of before the financial crisis which would also lend to efficient operations.

When comparing non-agricultural bank sizes, the results reveal that efficiency increases with size as large non-agricultural banks are the most efficient in this group with small non-agricultural banks being the least efficient. Large non-agricultural banks exhibit very high levels of efficiency with scores of 0.94, 0.97, and 0.98 before, during, and after the financial crisis respectively. During these time periods, medium sized non-agricultural banks have scores of 0.82, 0.84, and 0.87 while small non-agricultural banks exhibit the most inefficiency with scores of 0.80, 0.83, and 0.86.

The non-agricultural bank results contrast with the results of agricultural banks when drawing conclusions upon efficiency and bank size. With non-agricultural banks in North Dakota, efficiency increases with size, and banks would be able to increase their efficiency scores if they increase their size. This result is consistent with previous studies in that efficiency is related to bank sizes and larger banks are more efficient than smaller banks.

The results of non-agricultural banks agree with the agricultural bank findings when comparing time periods. The efficiency of non-agricultural banks of all sizes increases across the time periods. This result proves interesting as one would have assumed efficiency measures to be the most impacted and the lowest during the financial crisis. For non-agricultural banks, this result is harder to explain and would need further analysis in order to determine what may be affecting the efficiency scores during the financial crisis.

Overall, the efficiency scores show large non-agricultural banks to be the most efficient type of bank analyzed by the DEA model with an average efficiency across time of 0.96. It is also the most efficient bank during each individual time period being analyzed. Medium agricultural banks on the other hand exhibit the least efficiency of all the banks with an average efficiency over time of 0.81.

For all banks included in the study, efficiency could be reached by reducing inputs in the range of 4% - 19% depending on the type of bank. For example, this means for large non-agricultural banks inputs could be decreased by 4% to achieve efficiency while producing the same level of output. On the other hand, in order for medium agricultural banks to achieve efficiency without changing the output level, it should reduce inputs by 19% to achieve efficiency. This also means that over time banks reduced their input usage and more efficiently allocated their inputs to produce outputs.

Table 5.1 - Results

Type of Bank	*All Periods*	*Pre-Crisis*	*Crisis*	*Post-Crisis*
All Banks	0.831	0.8071712	0.8414731	0.8662923
Agricultural	0.8213419	0.7959955	0.8319949	0.8585962
Non-Agricultural	0.8582879	0.8380161	0.8676329	0.8875337
Small Ag	0.8244626	0.8024320	0.8297617	0.8594835
Medium Ag	0.8061248	0.7781122	0.8210726	0.8451817
Large Ag	0.8350730	0.8065943	0.8507968	0.8744281
Small Non-Ag	0.8212705	0.7972255	0.8335929	0.8551341
Medium Non-Ag	0.8360199	0.8165216	0.8413021	0.8666205
Large Non-Ag	0.9583023	0.9446742	0.9664322	0.9767314

CHAPTER 6: CONCLUSIONS

Data envelopment analysis can be a highly effective tool for measuring the efficiency of banking production processes. It calculates the relative efficiency of banks and creates a "best practice" frontier. DEA is applied to both agricultural and non-agricultural banks in the state of North Dakota and reveals inefficiencies in both types of banks.

Non-agricultural banks show higher efficiency scores than agricultural banks across all time periods analyzed in the study with an average efficiency of 0.86 compared to agricultural banks average efficiency of 0.83 with large non-agricultural banks having the highest efficiency and medium agricultural banks having the lowest efficiency score. The efficiency scores also increase over time for both types of banks. The average efficiency of agricultural banks before, during, and after the financial crisis are 0.80, 0.83, and 0.86 respectively. Before the financial crisis, non-agricultural banks exhibit an efficiency of 0.84 while during and after the financial crisis they have scores of 0.87 and 0.89 respectively. A means-variance test supports evidence of significant difference between the efficiency scores calculated.

Size does not seem to be a factor in the efficiency of agricultural banks as large banks are the most efficient while medium banks are the least efficient. However, the opposite is shown for non-agricultural banks as large banks are the most efficient and small banks are the least efficient. A regression analysis would need to be conducted in order to determine the magnitude of the relationship between the size of the bank and efficiency as well as the relationship between the type of bank, agricultural or non-agricultural, and efficiency.

For both agricultural and non-agricultural North Dakota banks, average efficiency increases across the time periods with the period after the financial crisis being the most efficient and the period before the financial crisis being the least efficient. These results are surprising as one would have assumed the efficiency during the financial crisis to be the lowest since the U.S. economy was in a recession and many banks failed during this time period. A regression analysis would be able to show any relationship between the time period being evaluated and banking efficiency.

Since the study only looks at North Dakota banks, it would be worthwhile to compare the efficiency of North Dakota banks to the efficiency of banks in another state during the same time periods. This would be able to show if North Dakota banks were efficient relative to banks of another state as the analysis does not provide an answer for this.

Another area of future research would be to include a measure that accounts for timing affects to further investigate the differences between efficiencies before, during, and after the financial crisis. This would be similar to including lagged variables in regression analysis to determine if efficiency is affected by past efficiencies or variables. This would be beneficial to determine if effects from the financial are still being felt after the crisis.

This research could also be furthered by using a cost or profit efficiency model as many regulators look to profitability to determine not only a bank's success but also the success of most businesses. In addition, the model could be added to by adding a variable that accounts for the risk averse behavior of banks. A risk-adjusted model may help to explain the differences between agricultural and non-agricultural banks as they have different policies for taking on risks and lending to customers. A risk-adjusted model would also be able to help explain differences between the different time periods, and may explain why efficiency increased over time as lenders became more risk averse.

Overall, the results of North Dakota banking efficiencies are consistent with previous banking studies. This study and others reveal that inefficiencies exist in the banking production process. This study is also consistent with the finding that non-agricultural banks are slightly more efficient than agricultural banks. It also shows that banks in North Dakota would be able to increase efficiency by reducing the amount of inputs used while still producing the same amount of output.

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APPENDIX A: DATA SUMMARY STATISTICS

Table A.1 – All Banks During All Periods

Variable	*Mean*	*Standard Deviation*
Total Deposits	$7,232,642.04	$58,365,580.62
Premises, Fixed Assets, and Capital Leases	80,900.11	582,738.54
Employees	2,264.71	16,757.31
Net Loans & Leases	6,577,155.38	49,645,657.01
Investment Securities	1,483,404.46	11,814,217.94

Table A.2 – Agricultural Banks During All Periods

Variable	*Mean*	*Standard Deviation*
Total Deposits	$102,439.82	$188,192.59
Premises, Fixed Assets, and Capital Leases	2,021.33	4,930.83
Employees	34.11	62.00
Net Loans & Leases	85,795.57	171,682.75
Investment Securities	22,257.79	34,289.28

Table A.3 – Small Agricultural Banks During All Periods

Variable	*Mean*	*Standard Deviation*
Total Deposits	$31,578.54	$11,610.57
Premises, Fixed Assets, and Capital Leases	424.83	442.63
Employees	10.68	3.50
Net Loans & Leases	21,044.22	9,155.28
Investment Securities	9,519.25	7,129.51

Table A.4 – Medium Agricultural Banks During All Periods

Variable	*Mean*	*Standard Deviation*
Total Deposits	$57,063.96	$22,233.06
Premises, Fixed Assets, and Capital Leases	774.79	629.01
Employees	19.49	7.34
Net Loans & Leases	40,722.77	18,332.05
Investment Securities	17,817.51	8,430.27

Table A.5 – Large Agricultural Banks During All Periods

Variable	*Mean*	*Standard Deviation*
Total Deposits	$341,282.26	$371,721.81
Premises, Fixed Assets, and Capital Leases	7,144.01	10,152.53
Employees	97.08	109.67
Net Loans & Leases	290,194.34	325,504.09
Investment Securities	66,823.23	66,957.38

Table A.6 – Non-Agricultural Banks During All Periods

Variable	*Mean*	*Standard Deviation*
Total Deposits	$26,947,027.88	$110,849,930.20
Premises, Fixed Assets, and Capital Leases	299,433.87	1,101,169.99
Employees	8,431.26	31,697.48
Net Loans & Leases	24,525,844.83	93,992,079.96
Investment Securities	5,520,877.76	22,426,532.01

Table A.7 – Small Non-Agricultural Banks During All Periods

Variable	*Mean*	*Standard Deviation*
Total Deposits	$184,380.57	$143,527.66
Premises, Fixed Assets, and Capital Leases	3,786.91	3,420.25
Employees	75.85	78.27
Net Loans & Leases	140,133.01	97,349.73
Investment Securities	51,591.68	67,684.95

Table A.8 – Medium Non-Agricultural Banks During All Periods

Variable	*Mean*	*Standard Deviation*
Total Deposits	$581,124.45	$276,441.92
Premises, Fixed Assets, and Capital Leases	15,006.82	8,872.05
Employees	304.95	235.79
Net Loans & Leases	447,274.05	181,610.55
Investment Securities	154,795.52	102,217.47

Table A.9 – Large Non-Agricultural Banks During All Periods

Variable	*Mean*	*Standard Deviation*
Total Deposits	$11,232,543.19	$204,870,126.04
Premises, Fixed Assets, and Capital Leases	1,222,559.35	1,985,452.34
Employees	34,622.78	57,384.11
Net Loans & Leases	101,388,934.40	170,643,476.64
Investment Securities	22,719,879.20	41,367,705.79

Table A.10 – All Banks During the Pre-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$4,578,596.42	$30,978,024.15
Premises, Fixed Assets, and Capital Leases	60,649.71	392,561.15
Employees	1,766.59	12,121.08
Net Loans & Leases	4,530,107.85	29,707,372.43
Investment Securities	858,875.89	5,586,418.57

Table A.11 – Agricultural Banks During the Pre-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$69,512.22	$120,303.56
Premises, Fixed Assets, and Capital Leases	1,373.69	3,049.62
Employees	27.86	46.39
Net Loans & Leases	58,610.76	113,310.93
Investment Securities	16,684.16	24,074.32

Table A.12 – Small Agricultural Banks During the Pre-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$26,862.26	$8,863.33
Premises, Fixed Assets, and Capital Leases	361.57	295.79
Employees	10.74	3.63
Net Loans & Leases	18,205.57	7,690.21
Investment Securities	8,892.30	6,059.23

Table A.13 – Medium Agricultural Banks During the Pre-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$45,534.14	$12,897.40
Premises, Fixed Assets, and Capital Leases	699.18	575.60
Employees	18.78	6.66
Net Loans & Leases	33,565.97	11,356.99
Investment Securities	14,460.10	6,571.92

Table A.14 – Large Agricultural Banks During the Pre-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$186,283.37	$209,999.72
Premises, Fixed Assets, and Capital Leases	4,283.25	5,333.43
Employees	74.00	79.91
Net Loans & Leases	172,292.40	195,310.41
Investment Securities	35,186.94	43,625.66

Table A.15 – Non-Agricultural Banks During the Pre-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$17,023,668.82	$583,325,423.47
Premises, Fixed Assets, and Capital Leases	224,251.50	737,350.12
Employees	6,565.49	22,841.97
Net Loans & Leases	16,871,439.83	55,812,448.97
Investment Securities	3,183,325.07	10,494,302.55

Table A.16 – Small Non-Agricultural Banks During the Pre-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$129,441.81	$79,568.66
Premises, Fixed Assets, and Capital Leases	2,879.25	2,008.16
Employees	57.07	37.66
Net Loans & Leases	103,823.54	60,053.57
Investment Securities	34,363.76	41,609.29

Table A.17 – Medium Non-Agricultural Banks During the Pre-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$423,765.95	$157,755.80
Premises, Fixed Assets, and Capital Leases	11,783.67	7,294.63
Employees	265.31	205.10
Net Loans & Leases	351,938.05	146,594.10
Investment Securities	117,408.46	62,006.20

Table A.18 – Large Non-Agricultural Banks During the Pre-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$70,178,676.21	$102,533,042.51
Premises, Fixed Assets, and Capital Leases	914,875.12	1,283,120.55
Employees	26,932.52	40,459.10
Net Loans & Leases	69,679,424.49	96,744,254.67
Investment Securities	13,058,150.42	18,229,688.71

Table A.19 – All Banks During the Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$6,501,752.36	$43,524,660.76
Premises, Fixed Assets, and Capital Leases	75,411.07	483,934.20
Employees	2,260.76	15,506.80
Net Loans & Leases	6,235,171.51	39,800,939.38
Investment Securities	1,432,124.83	9,612,319.87

Table A.20 – Agricultural Banks During the Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$98,377.69	$181,050.94
Premises, Fixed Assets, and Capital Leases	2,012.08	5,115.01
Employees	32.96	61.90
Net Loans & Leases	84,822.50	174,180.81
Investment Securities	20,391.26	27,619.93

Table A.21 – Small Agricultural Banks During the Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$32,099.75	$8,898.17
Premises, Fixed Assets, and Capital Leases	458.13	433.61
Employees	10.65	3.33
Net Loans & Leases	21,719.92	7,885.63
Investment Securities	9,384.94	7,150.68

Table A.22 – Medium Agricultural Banks During the Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$58,646.42	$17,815.56
Premises, Fixed Assets, and Capital Leases	813.63	655.20
Employees	19.59	7.55
Net Loans & Leases	43,215.21	17,042.05
Investment Securities	17,943.12	7,002.06

Table A.23 – Large Agricultural Banks During the Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$276,160.65	$309,146.71
Premises, Fixed Assets, and Capital Leases	6,525.31	9,087.30
Employees	92.82	106.26
Net Loans & Leases	258,972.22	295,310.34
Investment Securities	44,551.68	47,250.59

Table A.24 – Non-Agricultural Banks During the Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$23,982,965.19	$81,684,554.25
Premises, Fixed Assets, and Capital Leases	275,790.31	9,087.30
Employees	8,342.63	106.26
Net Loans & Leases	23,025,624.32	295,310.34
Investment Securities	5,286,157.48	47,250.59

Table A.25 – Small Non-Agricultural Banks During the Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$197,764.97	$121,801.11
Premises, Fixed Assets, and Capital Leases	4,177.64	3,262.21
Employees	74.57	51.69
Net Loans & Leases	158,900.17	96,163.66
Investment Securities	49,746.89	54,074.56

Table A.26 – Medium Non-Agricultural Banks During the Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$585,189.61	$171,921.84
Premises, Fixed Assets, and Capital Leases	15,894.48	9,591.06
Employees	297.80	204.70
Net Loans & Leases	496,618.23	137,089.84
Investment Securities	121,640.18	56,564.54

Table A.27 – Large Non-Agricultural Banks During the Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$98,850,770.48	$143,940,049.56
Premises, Fixed Assets, and Capital Leases	1,122,227.46	1,586,018.34
Employees	34,264.38	51,898.24
Net Loans & Leases	95,042,913.06	128,455,469.15
Investment Securities	21,784,248.83	31,818,915.18

Table A.28 – All Banks During the Post-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$12,420,773.21	$93,217,484.24
Premises, Fixed Assets, and Capital Leases	120,609.12	857,509.48
Employees	3,156.58	23,314.43
Net Loans & Leases	10,438,881.43	76,300,977.68
Investment Securities	2,622,760.62	18,976,597.70

Table A.29 – Agricultural Banks During the Post-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$119,983.32	$216,364.82
Premises, Fixed Assets, and Capital Leases	2,150.43	5,605.00
Employees	33.50	63.32
Net Loans & Leases	94,213.45	189,989.62
Investment Securities	27,610.06	39,699.55

Table A.30 – Small Agricultural Banks During the Post-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$39,228.33	$13,091.25
Premises, Fixed Assets, and Capital Leases	512.55	616.86
Employees	10.47	3.29
Net Loans & Leases	25,218.32	10,251.49
Investment Securities	10,833.26	8,569.91

Table A.31 – Medium Agricultural Banks During the Post-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$76,186.16	$24,259.41
Premises, Fixed Assets, and Capital Leases	881.24	684.37
Employees	20.65	8.16
Net Loans & Leases	51,585.52	22,792.48
Investment Securities	23,609.22	9,037.67

Table A.32 – Large Agricultural Banks During the Post-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$341,282.26	$371,721.81
Premises, Fixed Assets, and Capital Leases	7,144.01	10,152.53
Employees	97.08	109.67
Net Loans & Leases	290,194.34	325,504.09
Investment Securities	66,823.23	66,957.38

Table A.33 – Non-Agricultural Banks During the Post-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$46,288,948.03	$176,424,452.06
Premises, Fixed Assets, and Capital Leases	446,765.39	1,618,979.94
Employees	11,755.46	44,091.20
Net Loans & Leases	38,921,200.59	144,205,521.81
Investment Securities	9,768,075.15	35,848,261.67

Table A.34 – Small Non-Agricultural Banks During the Post-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$271,600.46	$191,478.27
Premises, Fixed Assets, and Capital Leases	5,114.83	4,763.18
Employees	109.57	122.47
Net Loans & Leases	191,163.13	122,000.83
Investment Securities	82,970.39	96,081.92

Table A.35 – Medium Non-Agricultural Banks During the Post-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$853,791.73	$284,349.84
Premises, Fixed Assets, and Capital Leases	20,055.54	8,481.99
Employees	379.08	285.38
Net Loans & Leases	581,215.93	165,826.75
Investment Securities	242,326.45	127,076.47

Table A.36 – Large Non-Agricultural Banks During the Post-Crisis

Variable	*Mean*	*Standard Deviation*
Total Deposits	$191,331,325.54	$320,947,411.79
Premises, Fixed Assets, and Capital Leases	1,827,894.67	2,914,206.15
Employees	48,319.67	80,017.23
Net Loans & Leases	161,111,257.63	260,100,255.39
Investment Securities	40,251,658.14	64,590,383.66

APPENDIX B: RESULTS SUMMARY STATISTICS

Table B.1 – Results (Means and Standard Deviations)

Type of Bank	*All Periods*	*Pre-Crisis*	*Crisis*	*Post-Crisis*
All Banks	0.831 (0.0742129)	0.8071712 (0.0680524)	0.8414731 (0.0668133)	0.8662923 (0.0737090)
Agricultural	0.8213419 (0.0654609)	0.7959955 (0.0573181)	0.8319949 (0.0570697)	0.8585962 (0.0843435)
Non-Agricultural	0.8582879 (0.0888030)	0.8380161 (0.0840249)	0.8676329 (0.0830070)	0.8875337 (0.0917091)
Small Ag	0.8244626 (0.0636137)	0.8024320 (0.0540189)	0.8297617 (0.0565174)	0.8594835 (0.0671696)
Medium Ag	0.8061248 (0.0697894)	0.7781122 (0.0632069)	0.8210726 (0.0614047)	0.8451817 (0.0641571)
Large Ag	0.8350730 (0.0591155)	0.8065943 (0.0499172)	0.8507968 (0.0472726)	0.8744281 (0.545771)
Small Non-Ag	0.8212705 (0.0788016)	0.7972255 (0.0629518)	0.8335929 (0.0679751)	0.8551341 (0.0949753)
Medium Non-Ag	0.8360199 (0.0699222)	0.8165216 (0.0645796)	0.8413021 (0.0707458)	0.8666205 (0.0674857)
Large Non-Ag	0.9583023 (0.0378393)	0.9446742 (0.0374556)	0.9664322 (0.0285486)	0.9767314 (0.0348227)

Table B.2 – Means-Variances Test

	Degrees of Freedom	*Mean Square*	*F Value*	*Pr > F*
Type of Bank	5	0.92801	256.21	< 0.0001
Time Period	2	1.30411	360.05	< 0.0001
Type of Bank * Time Period	10	0.00782	2.13	0.0176

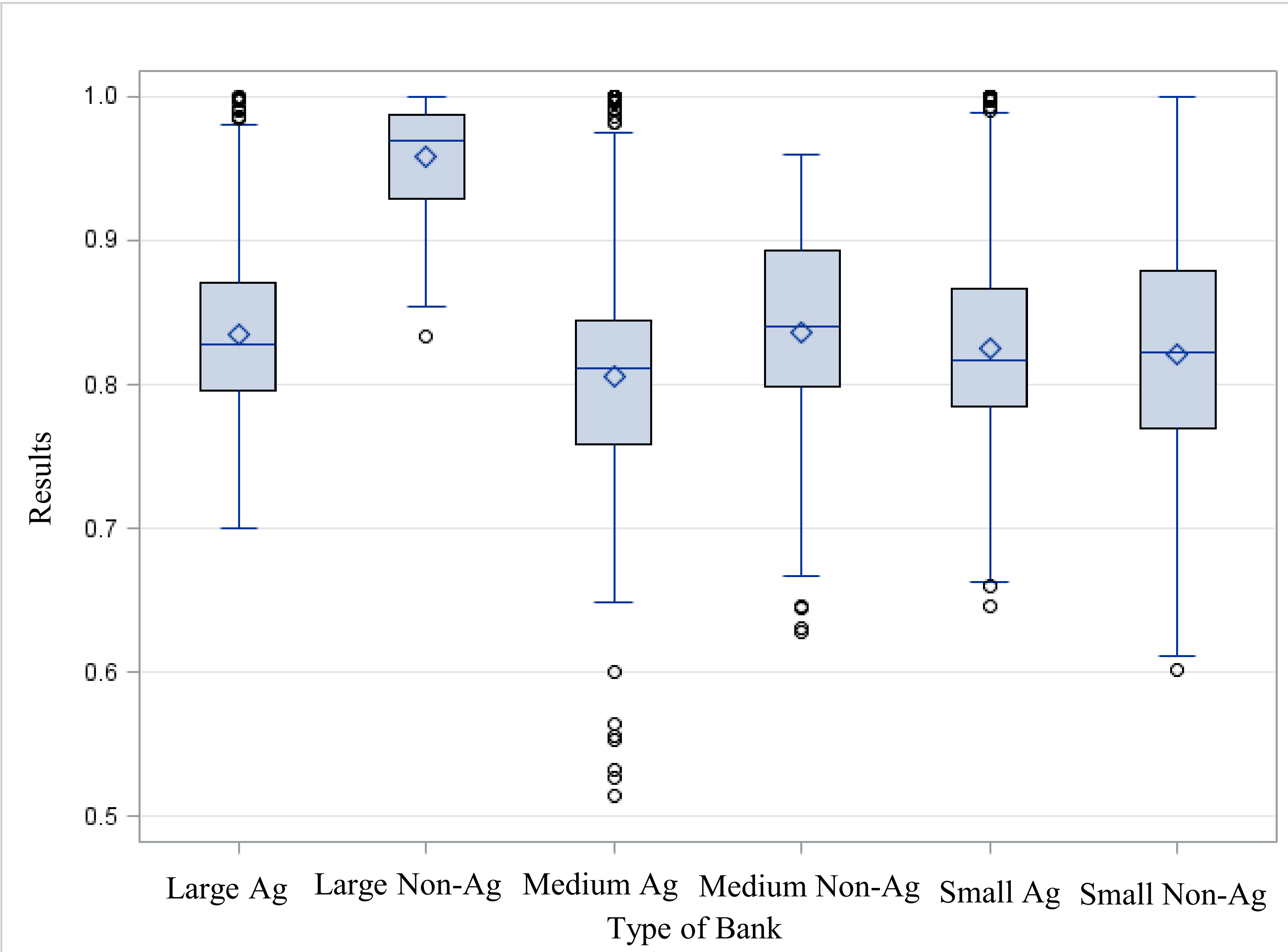

Figure B.1 - Distribution of Results by Type of Bank

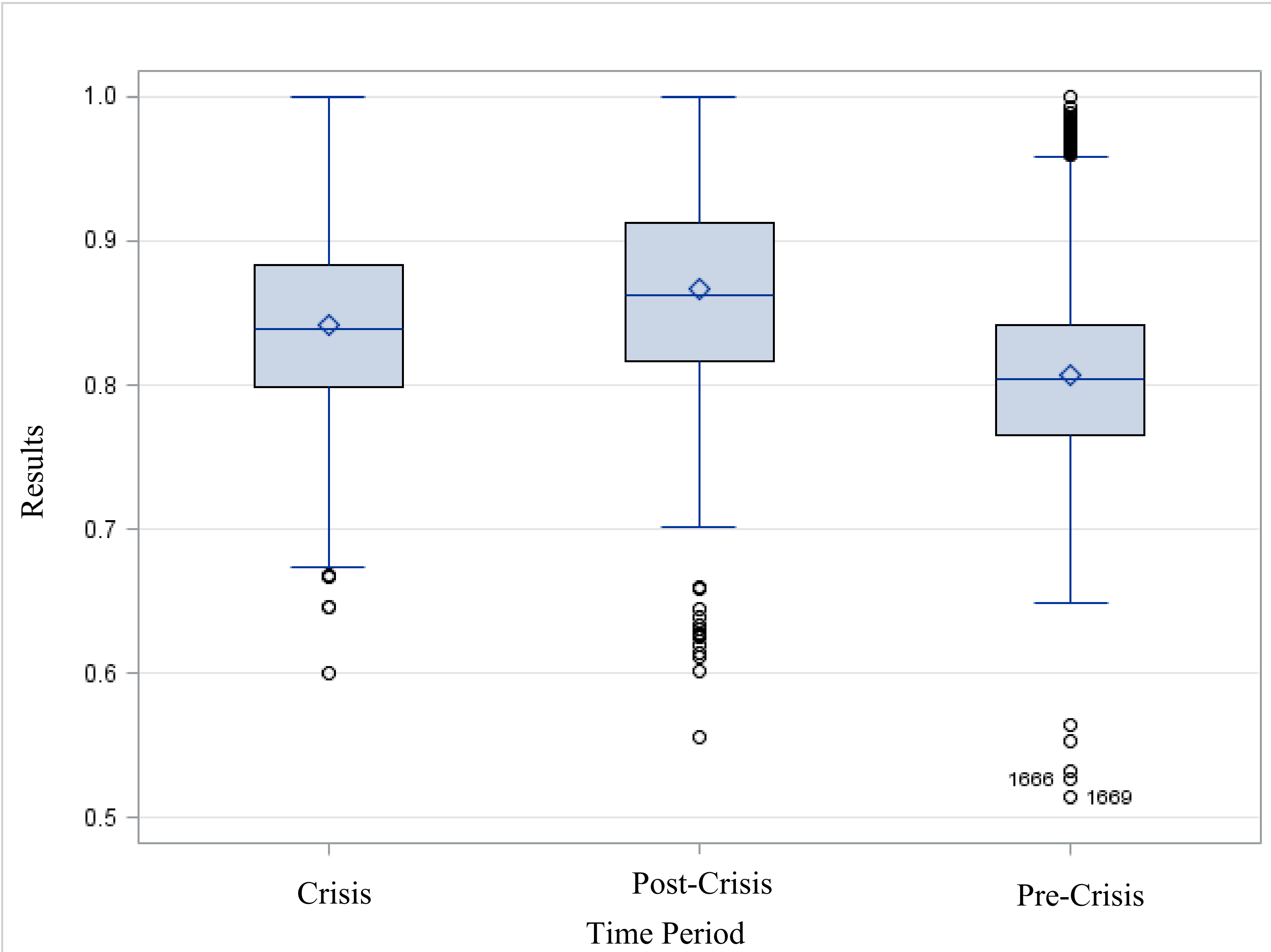

Figure B.2 - Distribution of Results by Time of Bank

Table B.3 – Tukey's Studentized Range (HSD) Test by Type of Bank

*Comparisons Significant at the 0.05 Level Are Indicated by ****			
Type of Bank Comparison	*Difference between Means*	*Simultaneous 95% Confidence Limits*	
Large Non-Ag – Medium Non-Ag	0.12228	0.10737	0.13719
Large Non-Ag – Large Ag	0.12323	0.11040	0.13606
Large Non-Ag – Small Ag	0.13384	0.12192	0.14576
Large Non-Ag – Small Non-Ag	0.13703	0.12363	0.15043
Large Non-Ag – Medium Ag	0.15218	0.13977	0.16458
Medium Non-Ag – Large Non-Ag	-0.12230	-0.13720	-0.10740
Medium Non-Ag – Large Ag	0.00095	-0.01120	0.01309
Medium Non-Ag – Small Ag	0.01156	0.00038	0.02274
Medium Non-Ag – Small Non-Ag	0.01475	0.0020	0.02750
Medium Non-Ag – Medium Ag	0.02990	0.01820	0.04159
Large Ag – Large Non-Ag	-0.12320	-0.13610	-0.11040
Large Ag – Medium Non-Ag	-0.00090	-0.01310	0.01120
Large Ag – Small Ag	0.01061	0.00241	0.01882
Large Ag – Small Non-Ag	0.01380	0.00357	0.02404
Large Ag – Medium Ag	0.02895	0.02006	0.03784
Small Ag – Large Non-Ag	-0.13380	-0.14580	-0.12190
Small Ag – Medium Non-Ag	-0.01160	-0.02270	-0.00040
Small Ag – Large Ag	-0.01060	-0.01880	-0.00240
Small Ag – Small Non-Ag	0.00319	-0.00590	0.01226
Small Ag – Medium Non-Ag	0.01834	0.01081	0.02586

Table B.3 – Tukey's Studentized Range (HSD) Test by Type of Bank (continued)

*Comparisons Significant at the 0.05 Level Are Indicated by ****			
Type of Bank Comparison	*Difference between Means*	*Simultaneous 95% Confidence Limits*	
Small Non-Ag – Large Non-Ag	-0.1370	-0.15040	-0.12360
Small Non-Ag – Medium Non-Ag	-0.01470	-0.02750	-0.0020
Small Non-Ag – Large Ag	-0.01380	-0.0240	-0.00360
Small Non-Ag – Small Ag	-0.00320	-0.01230	0.00588
Small Non-Ag – Medium Ag	0.01515	0.00545	0.02484
Medium Ag – Large Non-Ag	-0.15220	-0.16460	-0.13980
Medium Ag – Medium Non-Ag	-0.02990	-0.04160	-0.01820
Medium Ag – Large Ag	-0.02890	-0.03780	-0.02010
Medium Ag – Small Ag	-0.01830	-0.02590	-0.01080
Medium Ag – Small Non-Ag	0.01510	-0.0248	-0.00540

Table B.4 – Tukey's Studentized Range (HSD) Test by Time Period

*Comparisons Significant at the 0.05 Level Are Indicated by ****			
Time Period Comparison	*Difference between Means*	*Simultaneous 95% Confidence Limits*	
Post-Crisis – Crisis	0.02482 ***	0.01818	0.03146
Post-Crisis – Pre-Crisis	0.05912 ***	0.05385	0.06439
Crisis – Post-Crisis	-0.02480 ***	-0.03150	-0.01820
Crisis – Pre-Crisis	0.03430 ***	0.02826	0.04035
Pre-Crisis – Post-Crisis	-0.05910 ***	-0.06440	-0.05390
Pre-Crisis - Crisis	-0.03430 ***	-0.04030	-0.02830

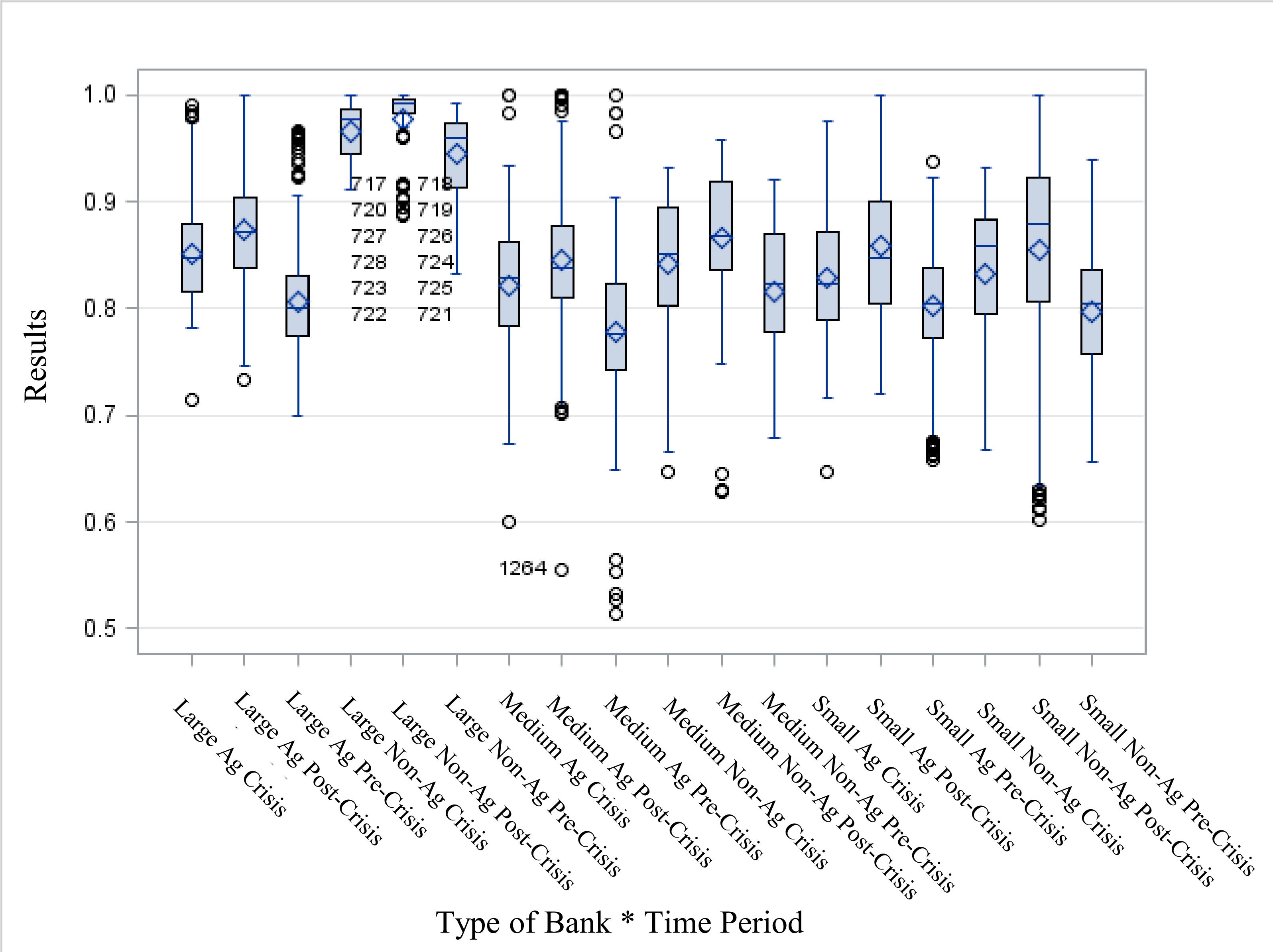

Figure B.3 – Distribution of Results by Type of Bank and Time Period