ESSAYS ON BANKING MERGERS AND ACQUISITIONS

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ABSTRACT

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This dissertation includes three chapters which are three papers on banking mergers and acquisitions. Bank failure and bank takeover are major risks which cause a bank to cease to exist, and Chapter 1 focuses on analyzing the factors which indicate bank takeover target vs. bank failure. The target banks would be integrated into acquiring banks, and the performance of the acquiring banks may change post the takeovers. Therefore Chapter 2 focuses on the impact of bank acquisition on the acquiring bank in the U.S.. Chapter 3 focuses on the prediction field and compares two different methodologies (multinomial logistic regression and machine learning method of XGBoost) on the prediction of bank failure or takeover.

Chapter 1, titled FACTORS THAT INDICATE BANK TAKEOVER TARGET VS. BANK FAILURE, analyzes the mergers and acquisitions data for the US banking industry from 2001 to late 2015, using both multinomial logistic method and competing risk proportional hazard method, to see how the financial ratios and bank specific features affect the risk of bank failure, bank takeover by a correlated bank under the same ultimate parent bank holding company, and bank takeover by an independent bank with a different ultimate parent bank holding company. This chapter also analyzes the characteristics of failed banks and the target banks in different stages in the financial economic cycle. The results show that the failed banks or the banks which were taken over by independent banks have lower capital ratio, higher real estate loan ratio and commercial and industrial loan ratio, higher non-performing loan ratio, lower after tax profit ratio, higher operating profit ratio, higher liquidity ratio, younger age and smaller asset growth ratio than the baseline banks which continue to

operate as usual during the through the cycle period. One notable difference between these two risks is that failed banks tend to be of bigger size, while the acquired banks tend to be of smaller size. Banks which were taken over by correlated banks exhibit higher equity ratio, higher commercial and industrial loan ratio, lower after tax profit ratio, lower liquidity ratio, bigger size, smaller asset growth ratio and younger age compared to the baseline banks which continue to operate as usual during the through the cycle period. The results show the three risk events are subject to some extent of sensitivity to different stages in the financial economic cycle, with the risk of bank takeover by a correlated bank has most sensitivity. The results also show there is small sensitivity observed for the factors indicating the three risks to the methodology utilized.

Chapter 2, titled IMPACT OF BANK ACQUISITION ON THE ACQUIRING BANK IN THE U.S., focuses on the merger and acquisition activities in the U.S. banking industry between 2003 and 2014 and analyzes the data to see the effects of the merger and acquisition on the acquiring banks' performance post the event. This chapter selects performance measures of financial ratios implied in CAMEL measure, uses both group time difference-in-difference method and quantile difference-in-difference method to see the impacts. The results show that not all the financial ratios have been significantly impacted by the merger and acquisition, and the impacts show some variations depending on which stages in an economic cycle the mergers and acquisitions are conducted in. Equity ratio, commercial and industrial loan ratio, delinquent assets ratio, non-performing assets ratio and return on equity ratio show significant impact from the mergers and acquisitions for all the three stages across the economic cycle. The results also show that there are variations of merger and acquisition effects on the performance measures depending on whether they are in high end or low end of their distributions.

Chapter 3, titled PREDICTION OF U.S. BANK STATUS USING MACHINE

LEARNING VS. MULTINOMIAL LOGISTIC REGRESSION, compares multinomial logistic regression methodology with machine learning method of eXtreme Gradient Boosting (XGBoost), to see which methodology can give better prediction on two types of risk events faced by U.S. banks, namely bank failure and bank takeover, using the features consisting of financial ratios on the data from 2002 to 2014. This paper also compares the most important features in each methodology. Beyond that, this paper explores SHapley Additive exPlanations (SHAP) analysis to interpret how bank features influence these two types of risk events from XGBoost method. The results show that XGBoost method gives better prediction accuracy if both developing the model and evaluating the performance on the whole length of US banking mergers and acquisitions data from 2002 to 2014, but the outperformance of XGBoost method is not obvious if developing the model in restricted in-sample data (from 2002 to 2010) and evaluating the performance using the out-of-sample data (from 2011 and 2014). Both two methodologies can give better prediction accuracy on the risk of bank failure than the risk of bank takeover. In addition, the most important features from XGBoost method and multinomial logistic regression method are highly aligned, with non-operating expense ratio, net after tax income ratio, equity ratio, non-performing asset ratio are the top important features. Finally, the SHAP analysis on XGBoost model shows that the features contribute to the targeted risks in a non-linear way.

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To my husband Todd Clark, my parents, Min Wei and Qin Zheng, and my daughter Olivia Clark

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CHAPTER 1

FACTORS THAT INDICATE BANK TAKEOVER TARGET VS. BANK FAILURE

1.1 Introduction

The US banking industry has had significant mergers and acquisitions in the past 40 years. This paper studies the characteristics of the target banks, and attempts to determine what factors contribute to a bank failing, being taken over, or continuing as is. From January 1976 to September 2015, there have been 25,871 bank mergers and acquisitions in the U.S.. 3,462 banks were acquired due to failures. The majority of banks were acquired through complete mergers or purchases[1] and there were 22,306 acquisitions of this type. In general, both failed banks and the banks which are taken over by other banks can imply some extent of bank trouble. Besides bank trouble, the target of a bank takeover can also be healthy. Acquiring a failed bank can be different from acquiring a non-failed bank. An apparent distinguishable feature of acquiring a failed bank is that the government assists the acquisition process. For a non-failed bank, the target bank discusses and reaches the acquisition deal with the acquiring bank independently without the government intervention, thus the acquired bank is more independently analyzed by the acquiring bank and appeals to the acquirer to

[1] Non survivor transfers 95% or more of its asset to the acquiring bank

realize different goals. The different motivations and processes determine that the target of an acquisition may exhibit different characteristics conditional on whether it is a failed bank or a non-failed bank. The non-failed acquired bank which can either be acquired by a bank which is controlled by the same ultimate parent bank holding company[2], or be acquired by an independent bank which is controlled by a different ultimate parent bank holding company. If the acquiring bank has the same top bank holding company as the acquired bank, the deal may be influenced by the parent bank's strategic plan and reflects the consolidation of the potential inefficient resources. In contrast, if the acquiring bank and the acquired bank are independent and don't share the same top bank holding company, the deal is primarily operated to achieve specific goals for each side.

From January 2001 to September 2015, 7,784 banks have been consolidated through bank acquisitions. Among the target banks there are 715 failed banks and 7,069 non-failed banks. For the 7,069 non-failed target banks, 3,892 acquisitions are between independent banks, while 3,177 acquisitions are between correlated banks which have the same ultimate top bank holding companies. Figure 1.1 shows the amount of total acquisitions, as well as acquisitions distribution between failed banks and non-failed banks over the observation time. The amount of acquisitions on failed banks reached to a peak during the financial crisis period. In contrast, the acquisitions on non-failed banks were relatively less active during the financial crisis period. It is in line with the nature of financial crisis.

This paper aims to analyze the attributes of failed banks and the banks which have been acquired either by correlated banks or independent banks, and the results can imply insights to the banks which plan to avoid such events, as well as to the banks from the acquiring side to look for the potential targets. It provides empirical evidence to what factors impact the likelihood that the US banks would be acquired either

[2]In this case, the acquiring bank and the target bank are eventually controlled by the same conglomerate.

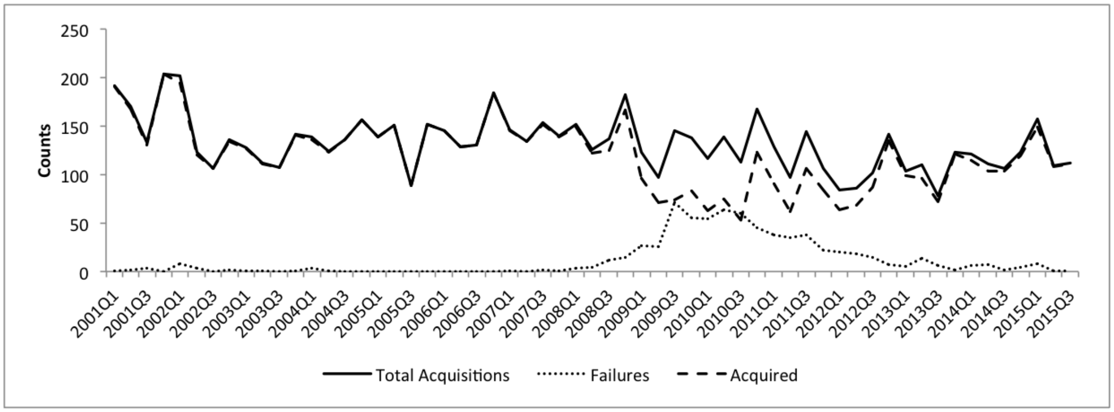


Figure 1.1: Acquisition Counts Across Time

because of failure or otherwise. The analysis on non-failed bank targets are further differentiated by whether the acquirer is a correlated bank or uncorrelated bank with the targets. The reason to analyze the bank takeover by a correlated bank lies in the fact that a bank faces takeover risk not only from external competitors, but also from internal competitors which are subject to the top parent bank's strategy. The outcome would be similar to the other two risk events to some extent, such as there would be less numbers of banks in the market, the top parent bank of acquiring would realize the strategic goal, etc. This treatment enables this paper to be differentiated from existing literature on including the analysis of risk of being acquired by a correlated bank and thus provide the empirical evidence to understand this risk event. This paper analyzes the US bank mergers and acquisitions data from January 2001 to September 2015, using both multinomial logistic regression and competing risk proportional hazard method, to see how the financial ratios affect the risk of bank failure and bank takeover. The financial ratios used in this paper are implied by CAMEL (Capital adequacy, Asset quality, Management, Earnings and Liquidity), which is a collection of five financial measures representing bank operation soundness proposed by the regulators. In addition to the bank specific financial characteristics implied by CAMEL measure, I include five other covariates. The list of the five other covariates includes specific bank characteristics such as bank age, bank asset size and asset growth, to remove bank specific factors; it also includes the environment faced by individual bank in terms of the competitiveness in the local market (represented by HHI index in the local market at county level calculated using deposit shares by each bank) and the indicator whether a bank has foreign branches or not. This paper is focused on both failed banks and acquired bank, and investigates how the characteristics mentioned above contribute to the likelihood for the bank failure or takeover.

The results show that the failed bank or the bank which was taken over by an independent bank has lower capital ratio, higher real estate loan ratio, higher commercial and industrial loan ratio, higher non-performing loan ratio, lower after tax profit ratio and higher liquidity ratio than the baseline banks which didn't undergo any of the three risk events during the whole observation period. The banks which were taken over by correlated banks exhibit higher equity ratio, higher commercial and industrial loan ratio, lower after tax profit ratio, and lower liquidity ratio compared to the banks in baseline state. The results show the three risk events are subject to some extent of sensitivity to different stages in the financial economic cycle, with the risk of bank takeover by a correlated bank has most sensitivity. The results also show there is some sensitivity observed for the factors indicating the three risks to the methodology utilized.

The contributions of this paper are three fold. First, the data sample duration spans from pre-credit crisis, during-credit crisis and post-credit crisis stages of the recent financial cycle. Hence this paper not only gives insights on how the financial ratios implied by CAMEL measure and other characteristics affecting the chance of the bank failure or takeover in a macroeconomic average view, but also gives an evolving view on how the determinants affect the chance of the bank failure or takeover under the three macroeconomic stages. Furthermore, it provides evidence that the target banks (failed banks or acquired banks) show some variation on the characteristics under different macroeconomic stages. Second, this paper investigates three different risks faced by a bank, namely bank failure, bank takeover by a bank under the same ultimate top bank holding company, and bank takeover by a bank that does not have the same ultimate top bank holding company as the acquired bank. Hence it enriches the risk event types in the bank mergers and acquisitions literature and broadens the understandings of the risk events determinants. Third, this paper provides empirical results evidence for different stakeholders to use. For instance, the results show that lower capital ratio would result in higher chance of bank failure, which supports the bank policy maker's decision of emphasizing capital ratios for individual banks. In addition, the failed banks exhibit higher bad assets ratio in terms of higher other real estate owned ratio, higher delinquent loan ratio and higher non-performing loan ratio, thus it provides the evidence for both individual banks and financial regulators to increase monitoring and supervising on the banks bad assets. While high liquidity ratio can both imply enough liquidity and that the bank doesn't use the cash efficiently to boost profit, the banks can take the insights from that both failed banks and takeover targets by independent banks exhibit higher cash rate.

1.2 Literature Review

The analysis on the mergers and acquisitions has received wide attention among the scholars from all the industries. Haleblian et al (2009) [20] conducted a review and research agenda on what we know about the mergers and acquisitions (M&As). The review on mergers and acquisitions from multi-disciplines has shed light on why there is research interest in this area and on what angels the research focuses on. The popularity of research on mergers and acquisitions field is not only driven by the large amount of the mergers and acquisitions (Barkema & Schijven, 2008 [5]), but also driven by that the analysis of these corporate behaviors can provide better understanding of the motivations of why firms seek M&As. Firms conducting mergers and acquisitions are driven by the motivations, among which the most intuitive motivation is value creation. Research on mergers and acquisitions in banking industry is seen to analyze the bank mergers by examining the effects on the acquiring bank efficiency, productivity and other value creation ways. For example, Berger et al (1998) [7] found that on average bank mergers increase the acquirers' profit efficiency relative to other comparative banks, while the cost efficiency effect for the acquirers is immaterial using the data of bank mergers of the 1990s. Another example is that Vij (2019) [39] found the acquirers which acquire failed banks can create immediate value: for a bank whose equity is traded public, the announcement average abnormal return is around 1.7%.

There are other research strands which are also worth exploring, such as to examine what elements may affect the likelihood the bank engage in acquisitions as either the acquired side or acquiring side, as well as quantifying these impacts. Toward the banks which engage in acquisitions as the acquiring side, which I do not explore, O'Keefe (1996) [34] found that in banking industry, the probability of engaging in mergers increases with bank size, bank liquidity as well as bank management, whereas the probability of engaging in mergers decreases with loan portfolio concentration. Wheelock and Wilson (2004) [40] have expanded the research to see the effects of regulators' supervision, market structure, and changes in regulation on the probability and the number of mergers a bank engages in as an acquirer, and found that supervisory evaluations of bank performance, in terms of CAMEL and CRA ratings, significantly affect expected mergers; the expected number of mergers is negatively related to the concentration of the market in which a bank is headquartered.

For the analysis of factors indicating the banks engage in acquisitions as the acquired side, which is part of this paper's focus, the samples of bank acquisitions analyzed among the existing literature date back as early as 1970. Hannan and

Rhoades (1987) [22], using a sample of Texas banks in existence in 1970, found that the banks with larger market shares, lower capital-to-asset ratios and operating in urban areas were more likely to be acquired. Amel and Rhoades (1989) [3] found that all else equal, a bank's earning is negatively related to its likelihood to be acquired using a large nationwide sample of acquisitions occurring during the years between 1978 and 1983. Moore (1997) [32] analyzed the acquisitions which occurred between June 1993 and July 1996, restricted the sample to avoid counting acquisitions among the subsidiaries of the same top bank holding company as an acquisition, and found that the likelihood of bank takeover is negatively related to the target bank's share, return on assets and capital to asset ratio. Wheelock and Wilson (2000) [41] used a sample consisting of banks which were followed from 1984 to 1994, and studied the characteristics of banks which failed or were taken over. They found that the banks with low capital ratios and high cost-efficiencies are more likely to be absorbed. Hannan and Pilloff (2009) [21] used a sample of individual banks observed from 1996 to 2005, studied how various bank and market characteristics affect the risk of bank takeover, and they found that the banks with less profit and less capital to asset ratios are more likely to be acquired.

This paper focuses on the banks which fail or are acquired by other banks. I follow Wheelock and Wilson (2000) [41] in their treatment of capital adequacy in terms of equity ratio, most of the asset quality ratios, earning ratio in terms of net after tax income ratio, bank size and bank age variables; but I do not look at operating efficiency as a measure of management performance, instead I look at non-interest expense ratio as a measure of management performance, along with other different treatment such as including delinquent ratio, operating profit ratio, HHI index and whether the target bank has foreign deposits or not. Unlike Moore (1997) [32], this paper treats a bank takeover by a correlated bank with the same ultimate parent bank holding company as a separate risk event and includes this type of acquisitions into analysis. Thus there are three risk events: bank failure, bank takeover by an independent bank, and bank takeover by a correlated bank.

1.3 Methodology

There are three risk events, namely bank failure, bank takeover by an independent bank and bank takeover by a correlated bank. After any one of the three risk events, the target bank stops existing as the original bank. The target bank is either absorbed and would not function as an independent bank any more, or functions as a new bank after some restructures. Hence the banks can be regarded as facing the competing risks of failure, takeover by a correlated party and takeover by an independent party. If none of the three risk events happens, the bank would still exist and operate with continuity.

I utilize two methodologies which are suit for the purpose to analyze the characteristics of the failed banks and acquired banks. The first method is multinomial logistic model. It is a standard empirical method to analyze the effects of continuous covariates on categorical dependent variables. In this methodology, the three risk events are treated as being three categorical states, and the baseline state is the bank continuing without being subject to one of the three above mentioned types of termination. The second method is the competing risk proportional hazard model. It takes into account that effects from the covariates can be different on the three competing risks. Using these two methods can give more robust result of the factors that indicate bank takeover targets and bank failures, as well as provide the evidence of the result variations potentially coming from different methodologies used.

1.3.1 Multinomial Logistic Regression

The first methodology used to analyze how the independent variables affect the risk of bank failure or bank takeover is multinomial logistic model. The setup is in a standard form. Let Y_{it} denote the state indicator of bank i in period t and there are 4 states in total. $Y_{it} = 0$ means the bank i neither is acquired nor fails in period t. This category is treated as the baseline category. $Y_{it} = 1$ means the bank i fails in period t. This represents the risk event of bank failure. $Y_{it} = 2$ means the bank i is acquired by an independent bank in period t. This represents the risk event of bank takeover by an independent bank. Lastly, $Y_{it} = 3$ means the bank i is acquired by a correlated bank in period t. This represents the risk event of bank takeover by a correlated bank with the same ultimate parent bank holding company. Hence there are three risk event categories and one baseline category in my case. Let X_{it} denote a vector of the independent variables for bank i for period t, β_j is a vector representing the corresponding parameter estimates of the independent variables for risk event j. The independent variables used in this paper include financial ratios implied by CAMEL measures and some other bank specific characteristics variables such as bank age. The non-baseline category response probabilities are modeled as:

$$P(Y_{it} = j|X_{it}) = \frac{e^{X_{it}\beta_j}}{1 + \sum_{h=1}^{3} e^{X_{it}\beta_h}}, j = 1, 2, 3 \tag{1.3.1}$$

And the baseline category response probability is:

$$P(Y_{it} = 0|X_{it}) = \frac{1}{1 + \sum_{h=1}^{3} e^{X_{it}\beta_h}} \tag{1.3.2}$$

The odds ratio for each non-baseline category response relative to the baseline category response can be easily obtained by taking division of the corresponding probability equations. The sign of one parameter estimate in the vector of β_j can be interpreted as how the corresponding covariate affects the binary odds ratio between the risk state j and the baseline state of bank continuity.

1.3.2 Competing Risk Proportional Hazard Model

The second methodology used to analyze how the independent variables affect the risk of bank failure or bank takeover is competing risk proportional hazard model. The proportional hazard duration model was firstly proposed by Cox in 1972 [13], and has since been extended to many fields. I use a generalized version of the proportional hazard model to see how the time varying covariates affect risk hazards. When there is only one hazard, the relationship between a vector of time vary independent variables X_{it} for bank i at time t and the hazard risk $H_i(t)$ for bank i at time t is:

$$H_i(t|X_{it}) = H_0(t)e^{X_{it}\beta} \tag{1.3.3}$$

$H_0(t)$ is the unspecified baseline hazard which is the hazard faced by all the banks when all covariates are equal to zero at time t, $e^{X_{it}\beta}$ is the relative risk component which depends on the time varying covariates value X_{it} for bank i at time t and the corresponding parameter β.

This paper analyzes three hazards, and it uses the competing risk proportional hazard duration model with time varying covariates. For each one of the three bank risks, the hazard risk j (where $j = 1$ implies bank failure, $j = 2$ implies bank takeover by an independent bank, and $j = 3$ implies bank takeover by a correlated bank) is:

$$H_{ij}(t|X_{it}) = H_0(t)e^{X_{it}\beta_j}, j = 1, 2, 3 \tag{1.3.4}$$

The competing risks happen when the occurrence of any one hazard excludes each of the other two hazards. For example, bank failure and bank acquisition are exclusive, so if one happens, other does not. The non-failed bank acquired by a correlated bank will make it impossible to be acquired by an independent bank. Under the competing risk circumstances, for each of the three hazard risks, the hazard risk equation is estimated separately and it yields separate coefficients β_j for the risk j. If a bank i experiences one hazard event at time t, then this bank is considered to be truncated at time t for the other two risks. The competing risk proportional hazard model setup introduced above can allow the research to focus on the analysis of the characteristics of the banks experiencing each one of the three risks.

1.4 Data and Specification of Covariates

There are two main data sets collected from two sources. The first data set regards to the banking merger and acquisition activities and it was obtained from National Information Center (NIC) maintained by Federal Reserve Board. This data contains basic information about acquiring banks and the acquired banks. It provides the fields to identify whether the acquired bank fails or not. Hence the bank failure risk is identified from the data. The data also provides the information of the ultimate top bank holding companies for both the acquiring bank and the acquired bank, thus it enables the separation of the two risks that the bank was taken over by an independent bank or a correlated bank. This data also lists the details of each acquisition including the announcement date and real acquisition date. The time period was narrowed down to between January 2001 and September 2015. This data curtailment is for the consideration of balancing the difficulty existing in the data collection process and the meaningful implication achieved in this research. The curtailed data contains a full macroeconomic cycle, which provide the data source for analysis on different stages across recent economic cycle.

The second data source is from the FDIC reports. There are two types of FDIC reports which provide the data used in this paper. The first report is FDIC call report, which provides data of the bank level financial ratios, such as all the financial ratios implied by CAMEL measures. The most granular frequency of the call reports is quarterly and the financial ratios are collected for the quarters between 2001Q1 and 2015Q3. The second report is FDIC all report, which provides the information of the bank's age and the detailed bank's operating location down to the county level. The bank's operating location is used to find out the number of the banks existing in each local market, combined with the information of the size for each bank in that local market, it is enables to calculate the local market competitiveness faced by banks represented by HHI indices.

All the data sets were merged together for analysis. In terms of financial information, this paper extracts financial ratios of five categories, which are collectively called CAMEL in the industry, from call reports. These five categories are capital adequacy (C), asset quality (A), management (M), earnings (E) and liquidity (L). The five categories can give an extensive measure of the banks operating health condition. The definition for each variable implied by CAMEL measures used in this paper is given in Table 1.1.

The capital adequacy ratio chosen in this paper is equity ratio. High equity ratio implies high capital adequacy. Capital adequacy can contribute different impacts on the risk of bank failure as opposed to bank takeover. It is expected that the capital ratio is negatively correlated to the risk of bank failure. Capital is the source for banks to absorb unexpected loss. Higher capital level provides higher buffer for banks under stressed period. As capital goes below zero, a bank becomes insolvent and would fail. The regulators have requirement for the banks to hold minimum capital ratio. When capital falls below the required ratio, a bank typically faces punitive measures, such as subject to capital directives by the FDIC to increase capital. For the risk of bank takeover by an independent bank, low capital ratio may not be attractive to the potential acquiring bank as: (1) the acquisition may require immediate capital

Table 1.1: CAMEL Financial Ratios Definition

Name	Definition
Capital Adequacy	
EquityRatio	total equity / total assets
Asset Quality	
TotalLoan	total loans/total assets
ReLoan	real estate loans/total loans
CniLoan	commercial and industrial loans/total loans
OtherRe	other real estate owned / total assets
Delinquent	past due 30 days through 89 days and still accruing/total assets
NonPerforming	non-performing loans/total assets
Management	
NonOperatingExp	non-interest expense / total assets
Earnings	
PAT	net after tax income / total assets
OperatingProfit	(net interest income - operating expenses)/total interest income
Liquidity	
CashRate	(federal funds purchased and securities purchased under agreements to resell - fed funds sold and securities sold under agreements to repurchase) /total assets

investment to meet regulatory standard, such as minimum capital ratios; (2) low capital ratio also implies the bank more susceptible to the stress, thus it may require more efforts for acquiring bank to operate after acquisition. However the target bank with low capital ratio can also be appealing to the acquiring banks as the target bank is likely to provide little resistance to an offer. In addition, the banks with low equity ratio may seek to sell as these banks may not have the ability to raise any more equity to grow and thus selling is a way to go, or they don't want to deal with any more regulatory pressure to increase equity. Hence capital adequacy's impact on the risk of bank takeover by an independent bank can be mixed. The relationship between capital adequacy and the risk of bank takeover by a correlated bank can also be mixed. In one hand, low capital adequacy can trigger the parent bank to take consolidation strategy to remediate the adverse situation. In the other hand, the parent bank may want to take action to let one subsidiary bank acquire a high capital adequacy bank to achieve the goal of synergy.

Asset quality measures the risks implied in different asset types for the banks. Sound asset quality means the assets held by a bank exhibit low risk of value depreciation or loss. I use six ratios to represent asset quality for a bank. A typical bank's major asset consists of different loans. The first four asset quality ratios are measures of the loan compositions for a bank: (1) Total Loan Ratio (TotalLoan): it is the ratio of total loans divided by total assets, which reflects traditional loan business activity by banks. (2) Real Estate Loan Ratio (ReLoan): it is the ratio of real estate loans divided by total loans. The amount of real estate loan is usually considerable for a typical bank, and the risk implied in real estate loan is different from other loans. (3) Commercial and Industrial Loan Ratio (CniLoan): it is the ratio of commercial and industrial loan divided by total loans. As commercial and industrial loan consists of the loans made to different industries, ideally using more segmented loan ratios by grouping the loans across industries with similar risk levels would be beneficial for the analysis. However the data retrieving work on bank loans across different industries is challenging , and banks normally would consider the benefit of diversification. Therefore I don't segment commercial and industrial loan ratio further. Both real estate loans and commercial and industrial loans are major component loans for banks. The distribution of the real estate loans and commercial and industrial loans can also appeal to buyer to realize the asset expansion on the specific areas. (4) Other Real Estate Owned Ratio (OtherRe): it is the ratio of other real estate owned divided by total assets, where the increase of other real estate owned is normally a result of foreclosure on real estate property when the borrowers default on the collateral loans. The other two ratios in asset quality category both reflect the assets that past due. The delinquent loan refers to the loan which is past due for less than 90 days, although is still accruing, it has the possibility to go into default. The non-performing loan refers to the loan which is past due for over 90 days, and it has a significantly higher possibility to go into default than the delinquent loan. To separate the two past due loans can give better understanding the characteristics of the banks experiencing the risk events considering the different default rates from these two types of loans. The higher the two ratios are for a bank, the more negative signal the bank sends in term of asset quality and risk.

For the management quality, I select non-operating expense ratio to represent this category. To estimate non-operating expense, I use the ratio of non-interest expense relative to total assets as the instrument. The non-interest expense includes multiple items which mainly are not directly related to funding sources used to make loans, such as salaries and employee benefits, expense of premises and fixed assets, etc. It can reflect bank's management in terms of cost management efficiency. Excessive high non-interest expense ratio can reflect the bank incurs high expense rather than the expense on traditional funding source such as deposits. This ratio also can reflect the activeness of the non traditional banking business. Thus it can also send a positive signal in terms of non operating activeness.

Two earning ratios are selected in this paper. The first one after tax profit ratio represents the bank's overall profit which includes both the operating and the non-operating profit. It is a comprehensive profit ratio which represents the bank's overall profitability. The second one is the ratio of the operating profit relative to total interest income, which represents how profitable the bank is to do the traditional banking business such as making loans. Both of them are positively related the bank's earning ability. As banks which fail or are taken over generally show some extent of trouble, hence a sensible expectation is that more profitable banks which have higher after tax profit ratio are less likely to be taken over or fail.

One liquidity ratio is analyzed in this paper and it is positively related to bank's liquidity. This liquid asset is calculated on the most liquid asset by taking the difference between federal funds purchased and securities purchased under agreements to resell and fed funds sold and securities sold under agreements to repurchase. Although this liquidity rate incorporates market making activities of larger regional banks, the specification of this variable reflects the net liquidity position from market making activities. The liquidity ratio defined in this paper can still represent the overall liquidity level across banks as the liquid asset calculated is a reliable source to provide liquidity. The interpretation of high liquidity can be of two folds. In one hand, any bank should maintain enough liquidity to pay off the upcoming short-term liability or for urgent use, thus it can avoid the event of bank run due to the lack of liquidity. In the other hand, short-term assets which provide high liquidity normally generate much lower revenue than longer-term assets such as loans. Hence excessive liquidity can signal too conservative liquidity strategy and thus generates low profit.

In addition to the CAMEL variables, I include five other covariates in the model. These five covariates include bank specific factors such as bank size (log of total assets), bank growth rate (year over year asset growth rate to estimate the percentage change from one year ago to the present) and bank age (log of target bank age), thus it can remove bank specific factor impact; and they also include the local market competitiveness for each bank (county level HHI index), and the indicator that whether the bank has foreign branches (using whether the bank has deposits from foreign branch as an instrument). The calculated county level HHI index can imply the market competitiveness facing by banks. The mergers can be limited for the anti trust consideration, however the existence of large players in the local markets can also phase other banks out. Whether a bank has foreign branches may play a role on the three risk hazards as well. In one way, acquiring a non-failed bank which has foreign branches can allow the acquiring bank to expand the market to the international footprint, which is especially attractive to the bank which does not have foreign branches but wants to expand in the international market. Hence a bank with foreign branches may be more appealing and likely to be acquired. In the other way, acquiring a bank with foreign branches can increase the governance work to additional regulators from the foreign markets, thus it may decrease appealing of a bank with foreign branches to the potential buyers. The banks with foreign branches may also be less likely to fail as they are diversified to broader market.

This paper uses the covariates' values of one year prior to the acquisition completion date as the independent variables' values, which considers the long duration of the bank acquisition approval thus it can reflect the actual characteristics about the failed banks or the acquired banks. When merging the banking mergers and acquisitions data with FDIC reports derived data, some acquisitions are dropped because there is no corresponding FDIC report information on the failed or acquired banks. This data exclusion may generate selection problems as not all the failed banks or takeover targets are included to the analysis. However, all regulated financial institutions in the U.S. are required to submit periodic financial information to the regulators, while FDIC call reports are important part of the required financial reports. The ones which don't have FDIC report information may not be good representatives for the U.S. banks, hence the impact of excluding the acquisitions where failed banks or takeover targets don't have FDIC reports is not material. With the data exclusion, there are abundant remaining acquisitions to provide meaningful results on what characteristics shared by acquired or failed banks via the three competing risks. Table 1.2 shows the statistics summary for the independent variables chosen for all the banks across the observation time.

Table 1.2: Summary Statistics for Explanatory Variables

Statistic	Observation	Mean	St. Dev.	Min	Max
EquityRatio	352,488	0.1	0.04	0.0	1.0

Table 1.2: (continued)

Statistic	Observation	Mean	St. Dev.	Min	Max
TotalLoan	352,488	0.6	0.2	0.0	1.0
ReLoan	352,488	0.7	0.2	0.0	1.0
CniLoan	352,488	0.03	0.1	0.0	1.0
OtherRe	352,488	0.004	0.01	0.0	0.3
Delinquent	352,488	0.01	0.01	0.0	0.4
NonPerforming	352,488	0.01	0.02	0.0	0.3
NonOperatingExp	352,488	0.02	0.02	−0.2	3.3
PAT	352,488	0.01	0.01	−0.6	0.5
OperatingProfit	352,488	0.03	6.3	−3,167.0	5.6
CashRate	352,488	0.02	0.1	−0.9	1.0
AssetSize	352,488	11.9	1.3	7.2	21.4
AssetGrowth	352,488	0.1	6.7	−0.9	2,658.1
Age	352,488	3.9	1.1	0.0	5.4
HHI	352,488	3,471.1	2,501.3	321.5	10,000
ForeignDepositFlag	352,488	0.02	0.1	0	1

1.5 Estimation Results

Two methodologies are used to estimate what characteristics the failed banks and acquired banks have. Under both methodologies, the financial characteristics implied by CAMEL and all the five other covariates are used as independent variables. The data length contains a full economic cycle from 2001Q1 to 2015Q3. The data can also be segmented into pre-credit crisis, during-credit crisis and post-credit crisis periods to see how the economy cycle affects the analysis.

1.5.1 Multinomial Logistic Method Results

Under multinomial logistic methodology, the analysis on the banks which undergo the three risk hazards is conducted in four segments of data: (1) Through The Cycle (2001Q1 - 2015Q3); (2) Pre-Credit Crisis (2001Q1 - 2007Q3); (3) During-Credit Crisis

(2007Q4 - 2009Q2) and (4) Post-Credit Crisis (2009Q3 - 2015Q3). Through the cycle time period covers one whole economic cycle, thus the analysis can provide average view in an economic cycle of indicators for each risk hazard. The other three stages segmented from total length of data are analyzed to see whether macroeconomic environment affects the relationships. This paper flags the duration of financial credit crisis from late 2007 to June 2009, hence the bank characteristics data during this period (2007Q4 to 2009Q2) is used as during-credit crisis period data. Intuitively, data prior to last quarter of 2007 is created as pre-credit crisis period data, while data post June of 2009 is created as post-credit crisis period data. Below sections discuss the model results for each of the four segments of data respectively.

1.5.1.1 Through The Cycle Results

All the financial ratio variables implied by CAMEL are statistically significant except operating profit rate from earning ability category for the risk of bank takeover by a correlated bank. Among the other variables, only HHI index is not statistically significant for two risks (bank failure and bank takeover by a correlated bank). Details of the estimation results for the through the cycle time period are shown in Table 1.3.

Table 1.3: Parameter Estimates - Multinomial Logistic Method - Through The Cycle

	Dependent variable:		
	Failure	TakeoverInd	TakeoverCor
EquityRatio	-37.556^{***}	-4.481^{***}	0.540^{***}
	(0.0001)	(0.0002)	(0.0002)
TotalLoan	4.144^{***}	-0.973^{***}	0.276^{***}
	(0.001)	(0.001)	(0.001)
ReLoan	1.856^{***}	1.197^{***}	0.081^{***}
	(0.001)	(0.001)	(0.001)
CniLoan	1.122^{***}	1.374^{***}	0.892^{***}
	(0.0002)	(0.0003)	(0.0004)
OtherRe	7.961^{***}	-3.698^{***}	-16.645^{***}
	(0.0002)	(0.00003)	(0.00001)

Table 1.3: (continued)

	Dependent variable:		
	Failure	TakeoverInd	TakeoverCor
Delinquent	23.945***	−17.789***	−4.222***
	(0.0001)	(0.00001)	(0.00002)
NonPerforming	17.626***	2.639***	−0.829***
	(0.001)	(0.0001)	(0.00002)
NonOperatingExp	−14.776***	3.332***	0.870***
	(0.0001)	(0.001)	(0.0004)
PAT	−13.680***	−8.367***	−2.519***
	(0.0002)	(0.0002)	(0.00002)
OperatingProfit	0.040***	0.053**	0.018
	(0.003)	(0.025)	(0.026)
CashRate	2.880***	1.410***	−1.153***
	(0.00001)	(0.0002)	(0.0001)
AssetSize	0.295***	−0.075***	0.099***
	(0.013)	(0.007)	(0.007)
AssetGrowth	−0.043***	−1.892***	−0.901***
	(0.002)	(0.001)	(0.001)
Age	−0.183***	−0.305***	−0.156***
	(0.045)	(0.020)	(0.021)
HHI	−0.00002	0.00003***	−0.00001
	(0.00002)	(0.00001)	(0.00001)
ForeignDepositFlag	−0.585***	−0.039***	−1.405***
	(0.0003)	(0.0002)	(0.0001)
Constant	−11.281***	−3.127***	−6.135***
	(0.001)	(0.0003)	(0.0003)

Note: *p<0.1; **p<0.05; ***p<0.01

The value in parenthesis is the variable's standard deviation.

Equity ratio affects risks of both bank failure and bank takeover by an independent bank in the same direction, to be specific, high equity ratio decreases the probability of these two risks. This is aligned with expectation for the risk of bank failure as higher equity ratio gives the banks higher buffer to absorb unexpected loss and thus the banks would be less likely to fail. It also provides the evidence on that the appealing from a bank with low capital ratio is high to an independent acquiring bank, and the bank with low equity ratio may have strong incentive to sell as the constraint on the ability for these banks to raise equity or they simply do not want to take more regulatory pressure to increase equity. It also provides the evidence that both failed banks and target banks on the takeover from an independent bank share similarity on the low equity ratio which can imply some extent of bank trouble. In contrast, high equity ratio increases the probability on the risk of bank takeover by a correlated bank. The result implies that the takeover between two correlated banks may be more subject to the strategic plans of the ultimate parent bank holding companies.

Among the four asset loan ratios, real estate loan ratio as well as commercial and industry loan ratio are both positively related to all the three bank risks. For the two risk types of bank takeovers, this can be interpreted as that the two types of loans are major composites of banks' assets and would attract the acquiring banks for asset acquisitions. For the risk of bank failure, the two ratios also positively affect this risk, which may reflect high risks implied in these assets. Specifically, the banks with higher real estate loan ratio has higher chance to fail which confirms the proximate cause for the financial crisis. The other two asset loans ratios don't affect the three risks in the same direction. The failed banks have higher total loan ratio and higher other real estate asset ratio. The higher other real estate asset ratio is a signal of higher foreclosure taken by the bank, which would increase the chance of bank failure. The banks which were taken over by independent banks have lower total loan ratio and lower other real estate asset ratio. The banks which were taken over by correlated banks have higher total loan ratio and lower other real estate asset ratio. For the two bad asset ratios, it is in line with the expectation that both delinquent asset and non-performing asset affect the risk of bank failure in the positive way. When these two bad asset ratios are high, it means the bank has low asset quality and thus it is more likely to fail. For the risk of bank takeover by a correlated bank, both delinquent asset ratio and non-performing asset ratio play a negative impact. It shows the acquisition target under this risk has better asset quality, and it further provides the evidence that the risk of bank takeover by a correlated bank is impacted by top bank holding company's strategy. For the risk of bank takeover by an independent bank, the target banks show lower delinquent asset ratio and higher non-performing asset ratio. The risk of takeover by an independent bank is more sensitive to the delinquent asset ratio than non-performing asset ratio. In sum, the probability of bank failure relative to base state has a very negative relationship to the credit quality variables while the risk of either bank takeover risk doesn't show the same with mixed directions of credit quality variable coefficients.

In terms of management efficiency, the failed banks show lower non-operating expense ratio than the banks which continue to operate, while the targets which experienced the two takeover risks show higher non-operating expense ratio. The negative relationship between the risk of bank failure and non-operating expense ratio implies the negative signal of high non-operating expense ratio is immaterial. For a bank which experiences difficulty, it may voluntarily reduce non-operating activities, hence it exhibits lower non-operating expense ratio. For the two risks of bank takeovers, the target banks exhibit high non-operating expense ratio, which implies these banks exhibit high activeness in the non-operating banking business. The targets of bank takeovers may have insufficient scale to cover fixed costs and cannot provide a sufficient return to investors, and therefore they are leaning to sell.

In terms of earnings ability, the two ratios have opposite impacts on the three risks respectively. To be specific, the target banks which experienced any one of the three risk events have lower total after tax profit ratio but higher operating profit ratio than the baseline banks which continue to operate. The three risk events are more sensitive to the after tax profit ratio than the operating profit ratio. For instance, increasing 1% of the after tax profit ratio would decrease the log odds ratio of bank failure relative to baseline state by 14%, while increasing 1% of the operating profit ratio would only increase the log odds ratio of bank failure relative to baseline state by 0.04%. The after tax profit ratio is a comprehensive measure to estimate the profitability, and all the target banks (the failed banks and the acquired banks) are observed to have lower total after tax profit ratio, which is consistent with ex ante expectation. It provides evidence that the more profitable banks may choose to operate as usual instead of being acquired.

In terms of liquidity ratio, failed banks and banks which are taken over by independent banks show higher cash rate, while banks which are acquired by correlated banks show lower cash rate. High liquidity ratio can both imply enough liquidity to send positive sign, and imply the banks don't use the cash efficiently to boost profit. The high liquidity ratio makes the banks more likely to experience the risks of bank failure and bank takeover by an independent bank.

The factors other than financial characteristics contained in CAMEL measure also display statistically significant impacts on these three risk events. Asset growth, bank's age since existence and the indicator whether the bank has foreign branches have shown same impacts in terms of parameter estimation signs on the three risk events. The higher the asset growth rate is, the less likely for the bank to experience failure or takeover. The older a bank is, the less likely for it to fail or experience takeover. The banks which have foreign branches are less likely to fail or be the targets of takeovers. Local market competitiveness in terms of county level HHI index is seen to be statistically significant for only risk of bank takeover by an independent bank. It shows that when the local market increases concentration on the big banks in this local market, the bank is more likely to be acquired by an independent bank. One distinguishable feature for the target bank in a takeover by an independent bank that smaller size of banks have large chance to be acquired The banks which experienced failure or takeover by correlated banks are estimated to have larger asset size, while the banks takeover by independent banks are estimated to have smaller asset size than the baseline banks which continue to operate as usual.

1.5.1.2 Pre-Credit Crisis Results

Table 1.4 presents the estimation results for the pre-credit crisis periods. The estimation result shows similar characteristics for the banks which experienced the three risk events in the pre-credit crisis time period and in the total length of observation period only with a few exceptions.

Table 1.4: Parameter Estimates - Multinomial Logistic Method - Pre-Credit Crisis

	Dependent variable:		
	Failed	AcquiredInd	AcquiredCor
EquityRatio	-16.237^{***}	-3.292^{***}	1.364^{***}
	(0.0002)	(0.0003)	(0.0002)
TotalLoan	7.466^{***}	-0.606^{***}	0.587^{***}
	(0.002)	(0.001)	(0.001)
ReLoan	3.912^{***}	1.138^{***}	0.064^{***}
	(0.002)	(0.001)	(0.001)
CniLoan	6.308^{***}	1.050^{***}	0.707^{***}
	(0.0002)	(0.0003)	(0.001)
OtherRe	42.903^{***}	4.250^{***}	10.714^{***}
	(0.00000)	(0.00000)	(0.00000)
Delinquent	13.407^{***}	-10.827^{***}	-10.992^{***}
	(0.00004)	(0.00003)	(0.00003)
NonPerforming	35.620^{***}	7.981^{***}	1.032^{***}
	(0.0001)	(0.00002)	(0.00002)
NonOperatingExp	2.775^{***}	3.597^{***}	0.944^{***}
	(0.0001)	(0.001)	(0.0002)
PAT	1.301^{***}	-6.891^{***}	-6.238^{***}
	(0.00001)	(0.0002)	(0.0001)
OperatingProfit	1.531^{***}	0.034	0.002
	(0.0003)	(0.027)	(0.021)
CashRate	9.973^{***}	1.212^{***}	-1.202^{***}
	(0.0001)	(0.0003)	(0.0002)
AssetSize	-0.097^{***}	0.049^{***}	0.223^{***}

Table 1.4: (continued)

	Dependent variable:		
	Failed	AcquiredInd	AcquiredCor
	(0.028)	(0.010)	(0.010)
AssetGrowth	-0.346^{***}	-1.706^{***}	-1.279^{***}
	(0.0002)	(0.002)	(0.002)
Age	0.139^{***}	-0.339^{***}	-0.108^{***}
	(0.008)	(0.029)	(0.028)
HHI	-0.00001	0.00004^{***}	-0.00001
	(0.0001)	(0.00001)	(0.00001)
ForeignDepositFlag	1.303^{***}	-0.302^{***}	-1.497^{***}
	(0.0002)	(0.0002)	(0.0001)
Constant	-16.445^{***}	-4.925^{***}	-7.855^{***}
	(0.002)	(0.0004)	(0.001)

Note: *p<0.1; **p<0.05; ***p<0.01

The value in parenthesis is the variable's standard deviation.

For the risk of bank failure in the pre-credit crisis period, all the variables are statistically significant except HHI index. The capital ratio, six financial ratios in the asset quality category, liquidity ratio, asset growth show same estimates signs in the pre-credit crisis period with the through the cycle estimates. In contrast, other covariates estimations in the pre-credit crisis period show opposite signs with the corresponding estimations from the through the cycle period. Among the ratios which show opposite signs in the pre-credit crisis period with through the cycle period estimations, non-operating expense ratio's effect on the risk of bank failure changes to be positive, which means high non-operating expense result in high probability of bank failure. Furthermore, the failed banks in the pre-credit crisis period exhibit higher after tax profit ratio, smaller asset size and older age than the baseline banks, and banks are more likely to be failed if they have foreign deposit. One thing to note is that there are not as many bank failures observed in the pre-credit crisis period as in the other time periods, hence it may explain that the estimation result shows some sensitivity in the pre-credit crisis period compared to through the cycle period estimation.

For the risk of bank takeover by an independent bank, one variable (operating profit ratio) lost statistic significance estimated in the pre-credit crisis period. All the financial ratios implied by CAMEL measure are estimated of the same signs with corresponding parameter estimations in the through the cycle period except other real estate asset ratio. In the pre-credit crisis period, the target banks with overall lower quality assets are more likely to be taken over by independent banks. The impacts from non CAMEL ratios are also aligned with the through the cycle estimates in terms of parameter signs except for asset size. Overall, the banks which were taken over by independent banks in the pre-credit crisis period exhibit similar patterns with through the cycle period, except that they show higher other real estate asset ratio and larger asset size than the banks which continue to operate as usual.

For the risk of bank takeover by a correlated bank in the pre-credit crisis period, like in the through the cycle period, two variables (operating profit ratio and HHI index) are not statistically significant. All the estimates are of the same signs in this time period as in through the cycle estimates except for two ratios in the asset composition and quality category, specifically other real estate asset ratio and non-performing asset ratio. The banks which are acquired by correlated banks exhibit higher other real estate asset ratio and higher non-performing asset ratio than the baseline banks which continue to operate as usual in the pre-credit crisis period.

1.5.1.3 During-Credit Crisis Results

Table 1.5 presents the estimation results from the during-credit crisis period. Compared to the through the cycle period estimates, during-credit crisis estimates show similar results in terms of covariates signs except several estimates, though the absolute values of covariates are different. Overall, among the three risk events, the risk of bank takeover by a correlated bank is affected mostly during-credit crisis period while the other two risks show comparable patterns with the through the cycle period estimates.

Table 1.5: Parameter Estimates - Multinomial Logistic Method - During-Credit Crisis

	Dependent variable:		
	Failed	AcquiredInd	AcquiredCor
EquityRatio	-47.425^{***}	-17.060^{***}	0.888^{***}
	(0.0001)	(0.001)	(0.0001)
TotalLoan	2.706^{***}	-0.657^{***}	1.554^{***}
	(0.001)	(0.003)	(0.002)
ReLoan	1.384^{***}	0.575^{***}	-0.132^{***}
	(0.002)	(0.003)	(0.001)
CniLoan	1.664^{***}	3.347^{***}	1.918^{***}
	(0.0004)	(0.003)	(0.001)
OtherRe	12.330^{***}	-4.518^{***}	-5.383^{***}
	(0.0001)	(0.0002)	(0.00003)
Delinquent	21.864^{***}	-16.151^{***}	2.187^{***}
	(0.0001)	(0.00003)	(0.00001)
NonPerforming	22.626^{***}	7.640^{***}	9.025^{***}
	(0.001)	(0.0004)	(0.0002)
NonOperatingExp	-1.359^{***}	-5.620^{***}	-2.764^{***}
	(0.00004)	(0.0002)	(0.00004)
PAT	-18.704^{***}	-19.194^{***}	-12.769^{***}
	(0.0002)	(0.001)	(0.0001)
OperatingProfit	0.966^{***}	-0.036	0.701^{***}
	(0.002)	(0.029)	(0.002)
CashRate	0.872^{***}	1.687^{***}	3.207^{***}
	(0.00005)	(0.001)	(0.0001)
AssetSize	0.340^{***}	-0.478^{***}	0.116^{***}
	(0.019)	(0.036)	(0.019)
AssetGrowth	0.047	-2.905^{***}	-0.610^{***}
	(0.046)	(0.002)	(0.004)
Age	-0.171^{**}	-0.040	-0.062
	(0.067)	(0.099)	(0.058)
HHI	-0.00005	-0.00003	-0.00002
	(0.00003)	(0.00005)	(0.00003)

Table 1.5: (continued)

	Dependent variable:		
	Failed	AcquiredInd	AcquiredCor
ForeignDepositFlag	-1.013^{***}	-210.776^{***}	-2.384^{***}
	(0.001)	(0.000)	(0.0001)
Constant	-8.864^{***}	1.410^{***}	-7.956^{***}
	(0.001)	(0.002)	(0.001)

Note: *p<0.1; **p<0.05; ***p<0.01

The value in parenthesis is the variable's standard deviation.

For the risk of bank failure, HHI index doesn't display statistic significance from the estimation during the credit crisis period. Besides HHI index, asset growth ratio loses significance when it is estimated in the during-credit stress period. It implies that during the credit stress period asset growth doesn't play much role as other variables on the risk of bank failure. All the other covariates affect this risk in the same direction as estimated in the through the cycle period. Banks are more likely to fail during the credit crisis period which is confirmed by that there were more observed bank failure during the credit crisis period. Hence it can explain why the covariates' signs are all consistent with the estimates from the through the cycle time period.

For the risk of bank takeover by an independent bank, three variables lose statistic significance during the credit crisis period. Among the three insignificant variables, operating profit ratio also loses significance in both the pre-credit crisis period and post crisis period. A variable can lose statistical significance and yet still be just as important as it ever was. The other two insignificant variables are bank age and HHI index. All the statistically significant variables affect the risk of bank takeover by an independent bank in the same direction during the credit crisis period as the through the cycle estimates, except non-operating expense ratio from management category. During the credit crisis period, higher non-operating expense ratio results in lower chance of bank takeover by an independent bank compared to the banks which continue to operate as usual.

For the risk of bank takeover by a correlated bank, like in all other periods, HHI index doesn't display statistic significance during-credit crisis period. This type of takeover happens between two banks under the same parent bank holding company, and the consequence of this takeover would not harm the fact that the consolidated assets are operated for the ultimate parent bank holding company. Hence the local market competitiveness may not be important to be considered for this takeover risk. Bank age also doesn't show statistic significance. Among the estimated significant variables, several variables affect the risk in the different directions from during-credit crisis period compared to estimates from other periods. Take the through the cycle estimates as benchmark, three variables in the asset composition and quality category, one variable in management category and the liquidity ratio affect the risk in different directions from estimation of during-credit crisis period. Among the three financial ratios in the asset quality category which change signs compared to through the cycle estimates, it is noticeable that the signs of delinquent ratio and non-performing asset ratio are positive during this period. The banks which experienced the risk of takeover by correlated banks have higher bad asset ratios during-credit stress period, which implies the parent bank holding companies are more active to consolidate the banks when they have more bad assets during-credit crisis period. The acquisition targets are also estimated to show higher liquid asset ratio and lower non-operating expense ratio than the baseline banks.

1.5.1.4 Post-Credit Crisis Results

Table 1.6 presents the estimation results from the post-credit crisis period. Overall, post-credit crisis period estimates show comparable results with the through the cycle estimates except for a few variables. Among the three risk events, the estimations for risk event of bank takeover by a correlated bank are seen to have most differences than the through the cycle period estimates.

Table 1.6: Parameter Estimates - Multinomial Logistic Method - Post-Credit Crisis

	Dependent variable:		
	Failed	AcquiredInd	AcquiredCor
EquityRatio	-45.329^{***}	-4.570^{***}	-1.117^{***}
	(0.00004)	(0.0001)	(0.0003)
TotalLoan	3.489^{***}	-1.089^{***}	-0.956^{***}
	(0.001)	(0.001)	(0.002)
ReLoan	0.167^{***}	1.286^{***}	0.531^{***}
	(0.001)	(0.001)	(0.001)
CniLoan	-0.573^{***}	1.481^{***}	0.944^{***}
	(0.00003)	(0.0005)	(0.001)
OtherRe	9.401^{***}	-7.006^{***}	-15.550^{***}
	(0.00004)	(0.0001)	(0.0001)
Delinquent	17.304^{***}	-18.438^{***}	-4.574^{***}
	(0.00002)	(0.00001)	(0.00002)
NonPerforming	14.579^{***}	1.186^{***}	3.198^{***}
	(0.0001)	(0.0001)	(0.0001)
NonOperatingExp	-18.700^{***}	1.291^{***}	1.240^{***}
	(0.00002)	(0.0001)	(0.001)
PAT	-8.650^{***}	-8.518^{***}	4.831^{***}
	(0.00001)	(0.0001)	(0.0001)
OperatingProfit	-0.014^{***}	0.006	0.037
	(0.004)	(0.018)	(0.049)
CashRate	4.214^{***}	2.543^{***}	-2.993^{***}
	(0.00001)	(0.0001)	(0.0002)
AssetSize	0.157^{***}	-0.156^{***}	-0.137^{***}
	(0.009)	(0.010)	(0.013)
AssetGrowth	-0.523^{***}	-1.909^{***}	-0.421^{***}
	(0.00004)	(0.0004)	(0.001)
Age	-0.245^{***}	-0.313^{***}	-0.292^{***}
	(0.002)	(0.030)	(0.038)
HHI	0.00000	0.00001	-0.00002
	(0.00003)	(0.00001)	(0.00002)
ForeignDepositFlag	-1.036^{***}	0.227^{***}	-0.512^{***}

Table 1.6: (continued)

	Dependent variable:		
	Failed	AcquiredInd	AcquiredCor
	(0.00001)	(0.0003)	(0.0002)
Constant	-6.854^{***}	-1.798^{***}	-2.475^{***}
	(0.001)	(0.0004)	(0.001)

Note: *p<0.1; **p<0.05; ***p<0.01
The value in parenthesis is the variable's standard deviation.

For the risk event of bank failure, only HHI index doesn't display statistic significance in the post-credit crisis period. The other variables affect this risk in the same directions as in the through the cycle estimates except commercial and industrial loan ratio in asset composition and quality category, and operating profit ratio in earning ability category. Unlike the estimated result in the through the cycle period, the banks which failed in post-credit crisis period exhibit lower commercial and industrial loan ratio and lower operating profit ratio than the baseline group.

For the risk event of bank takeover by an independent bank, two variables (operating profit ratio and HHI index) are not statistically significant. Except these two variables, all the other variables affect this risk in the same directions as in the through the cycle period, except the indicator whether the bank has foreign deposits. In the post-credit crisis period, a bank has a larger chance to be acquired by an independent bank if it has foreign deposits, which means the bank with foreign branches is more attractive to an independent acquirer to expand to foreign market in the post-credit crisis period.

For the risk event of bank takeover by a correlated bank in the post-credit crisis period, like through the cycle and pre-credit crisis period, operating profit and HHI index don't show statistic significance. Among the estimated significant variables, several variables affect the risk in different directions benchmarked with through the cycle estimates. Equity ratio in the capital adequacy category, two variables in the asset composition and quality category, after tax profit ratio in earning category and asset size measure are the ones which have different estimated signs in post-credit crisis period than through the cycle period. It provides evidence that post-credit crisis period the acquisitions between the correlated banks have undergone pattern changes compared to through the cycle, and this type of risk is more volatile to economy condition to reflect the parent banks active strategies.

1.5.2 Competing Risk Proportional Hazard Method Results

Besides multinomial logistic methodology, this paper also uses competing risk proportional hazard methodology. Competing risk proportional hazard method is used to the whole length of the observation data to see the through the cycle results. The estimated covariates from the three risk events are compared to the estimates using multinomial logistic method, so that the comparisons can provide the understanding of how sensitive the parameter estimates are to the methodologies used. The result shows that the banks which undergo each of the three risk events display similar characteristics in terms of the estimated signs of the covariates using both methodologies for the through the cycle period, though more variables show statistical insignificance using competing risk proportional hazard method. Table 1.7 shows the detailed parameter estimates from competing risk proportional hazard method.

Table 1.7: Parameter Estimates - Proportional Hazard - Through The Cycle

	Dependent variable:		
	Failed	AcquiredInd	AcquiredCor
EquityRatio	-41.050^{***}	-4.519^{***}	0.840
TotalLoan	2.678^{***}	-0.714^{***}	0.130
ReLoan	1.288^{***}	1.057^{***}	0.138
CniLoan	1.397^{*}	1.208^{***}	0.879^{***}
OtherRe	11.772^{***}	-6.655^{***}	-9.625^{**}

Table 1.7: (continued)

	Dependent variable:		
	Failed	AcquiredInd	AcquiredCor
Delinquent	16.387***	−11.376***	−5.919*
NonPerforming	16.302***	3.763**	2.091
NonOperatingExp	−11.771***	2.755***	−0.681
PAT	−4.622*	−7.733***	−4.612*
OperatingProfit	−0.013***	0.029	0.002
CashRate	1.217	1.729***	−1.328***
AssetSize	0.194***	−0.075**	0.115***
AssetGrowth	−0.297	−1.638***	−0.972***
Age	−0.228***	−0.312***	−0.150***
HHI	−0.00001	0.00002**	−0.00001
ForeignDepositFlag	−0.566	0.006	−1.210***
Note:		*p<0.1; **p<0.05; ***p<0.01	

For the risk event of bank failure, besides HHI index which loses statistic significance, there are three other variables which don't show statistic significance. These three additional variables include cash rate in the liquidity category, the growth ratio of asset and the indicator whether the bank has foreign deposits. The remaining statistically significant variables show the similar patterns in terms of parameter signs for the banks failure as estimated using multinomial logistic method except one earning ratio in terms of operating profit ratio. Under both methodologies, the failed banks exhibit lower equity ratio, higher delinquent assets ratio, higher non-performing assets ratio and lower after tax profit ratio than the banks in the baseline state. Unlike multinomial logistic method estimated result, higher operating profit ratio increases the chance of bank failure relative to the banks which continue to operate as usual from the competing risk proportional hazard method.

For the risk event of bank takeover by an independent bank, all the variables show the similar impact on this risk from competing risk proportional hazard method as multinomial logistic method, though two variables lose statistic significance. The two insignificant variables are operating profit ratio and the indicator whether the bank has foreign deposits. Capital ratio in terms of the equity ratio shows negative impact on the chance of this risk event. Among the six financial ratios in the asset composition and quality category, notably real estate loan ratio and commercial and industrial loan ratio are positively related to this risk event, and delinquent assets ratio is negatively related to this risk event. The non-operating expense ratio in the management category is positively related to this risk which implies the banks which were taken over by independent banks are active in the non-operating activities. Negative coefficient of after tax profit ratio shows that the banks acquired by independent banks display lower profit after tax, which implies these target banks are more vulnerable and easier to be acquired when they are not profitable. The liquidity ratio in terms of cash rate positively impacts this type of risk, which implies the independent acquiring banks are more interested in the targets with higher liquidity and also liquidity shortage is not the reason for the target banks seeking for takeovers. It also implies that a target bank in a takeover by an independent bank doesn't manage liquidity properly to generate profits which is evidenced by lower profit ratio of these target banks. For the non CAMEL variables, three variables (asset size, asset growth and bank age) are negatively related to this risk. Smaller, younger banks which don't expect high asset growth are more likely to be acquired by independent banks. In the meanwhile, the higher local market concentration is, the higher risk the bank faces to be acquired by an independent bank.

For the risk event of bank takeover by a correlated bank, there are in total seven variables which don't have statistic significance using competing risk proportional hazard method, among which two variables (operating profit ratio and HHI index) also lose statistic significance using multinomial logistic method. The capital ratio in terms of equity ratio, three ratios in the asset composition and quality category, non-operating expense ratio in management category are the others which don't show statistic significance. For the other variables, the estimated impacts on this type of risk using this method are of the same directions as multinomial logistic method estimates. A noticeable takeaway is that after tax profit ratio as well as cash rate in the liquidity category negatively impact this risk. In addition, banks with bigger asset size, lower growth ratio and younger history are estimated to be more likely to be acquired by a correlated bank compared to the baseline banks which continue to operate as usual. Furthermore, banks with foreign deposits are estimated to be acquired by a correlated bank with a smaller chance, which can be explained by that the parent bank already owns a bank with foreign branches hence doing such acquisition is less attractive to the whole parent bank's strategy.

1.6 Conclusion

This paper focuses on the three competing risks faced by banks, namely bank failure, bank takeover by an independent bank and bank takeover by a correlated bank. It uses both multinomial logistic methodology as well as competing risk proportional hazard methodology to analyze the characteristics for the banks which underwent these three risk events. By using the US banking mergers and acquisitions data from January 2001 to September 2015, it enables the analysis to be conducted to reflect both the macroeconomic average impact (through the cycle estimation) and the impacts in the different macroeconomic cycles (pre-credit crisis stage, during-credit crisis stage and post-credit crisis stage).

The banks which underwent the three competing risk events display different characteristics. The financial ratios implied by CAMEL measure and the other variables such as asset size, age, growth rate, HHI index of the bank's local market and whether the bank has foreign deposits, impact the three risk events differently in terms of both signs and magnitudes. For the through the cycle period, under both multinomial logistic methodology and competing risk proportional hazard methodology, the estimated results show that all the independent variables display similar impacts on each banking risk in terms of estimated parameter signs except a few variables. In addition, more variables lose statistic significance using competing risk proportional hazard method than using multinomial logistic regression method. In terms of the financial characteristics implied by CAMEL, the through the cycle estimation results show that the failed banks have lower equity ratio, higher asset loan ratios in terms of commercial real estate loan ratio and commercial and industrial loan ratio, higher delinquent asset ratio and non-performing asset ratio, lower non-operating expense ratio and lower after tax profit ratio compared to the baseline banks which continue to operate as usual using both methodologies. In addition, the failed banks exhibit larger asset size and younger age than the banks in baseline state. For the risk of bank takeover by independent banks, the through the cycle estimated results show that these target banks display lower equity ratio, higher commercial real estate loan ratio and commercial and industrial loan ratio, lower delinquent asset ratio, higher non-performing asset ratio, lower after tax profit ratio, higher non-operating expense ratio and higher liquidity ratio than the banks in baseline state under both methods. Furthermore, the banks which were taken over by independent banks are estimated to have smaller asset size, lower asset growth ratio and younger age. The banks are also more likely to be acquired by independent banks if they are in a more concentrated local market. For the risk of bank takeover by a correlated bank, the estimated results show that the target banks which underwent this risk event have higher commercial and industrial loan ratio, lower delinquent asset ratio, lower after tax profit ratio and lower liquidity ratio using both methodologies. Furthermore, these target banks which were taken over by independent banks are estimated to exhibit larger bank size, lower asset growth ratio and younger age. The banks are also less likely to be acquired by correlated banks if they have foreign deposits.

This paper also gives results of how the independent variables impact the three banks in different stages in a macroeconomic cycle using multinomial logistic method. The estimated results under the three macroeconomic cycle stages show some variations of how the independent variables impact the risks from the result from the through the cycle period. For the three competing risks, the risk of bank takeover by correlated banks shows most sensitivity to the macroeconomic cycles. It is in line with expectation as this risk of acquisition is mostly subject to the top parent bank's strategic plan and hence the impacts of financial characteristics on this type of risk may not be consistent across different macroeconomic cycles. For the risk of bank failure, the through the cycle period estimation results are highly consistent with during-credit crisis period estimates. It is also in line with expectation as many bank failures occur during-credit stress period, thus the through the cycle estimates are mostly driven by the bank failures in the credit stress period. For the risk of bank takeover by independent banks, the estimated results under different macroeconomic stages show least variations among the three risks. The bank takeover by an independent bank is most independent among the three risks as it doesn't involve any government involvement and it is also not subject to a single top parent bank's interference. Hence the characteristics of the banks which are taken over by independent banks are expected to have small sensitivity to macroeconomic cycles, which is consistent with this paper's result.

Overall, the analysis results show that the failed banks or the banks which were taken over by independent banks have lower capital ratio, higher real estate loan ratio and commercial and industrial loan ratio, higher non-performing loan ratio, lower after tax profit ratio, higher operating profit ratio, higher liquidity ratio, younger age and smaller asset growth ratio than the baseline banks which continue to operate as usual during the through the cycle period. One notable difference between these two risks is that failed banks tend to be of bigger size, while the acquired banks tend to be of smaller size. Banks which were taken over by correlated banks exhibit higher equity ratio, higher commercial and industrial loan ratio, lower after tax profit ratio, lower liquidity ratio, bigger size, smaller asset growth ratio and younger age compared to the baseline banks which continue to operate as usual during the through the cycle period. The results show the three risk events are subject to some extent of sensitivity to different stages in the financial economic cycle, with the risk of bank takeover by a correlated bank has most sensitivity. The results also show there is small sensitivity observed for the factors indicating the three risks to the methodology utilized.

CHAPTER 2

IMPACT OF BANK ACQUISITION ON THE ACQUIRING BANK IN THE U.S.

2.1 Introduction

The banking sector has gone through many consolidations. From early 2000 through late 2015, there have been over 7000 banking mergers and acquisitions in the U.S. to reshape the current banking industry status. The banking sector, as one of the most influential sectors in the economy, influences not only the banks which are operating entities in this sector, but also many other entities such as consumers and companies from different industries as borrowers. Therefore, the activities within this sector draw many research interests.

This paper focuses on the U.S. banking sector, analyzes the mergers and acquisitions between U.S. banks to see how the performance of acquiring banks changes after those mergers and acquisitions. The performance measures can take different forms. The impact study of this paper is focused on a relevant set of variables implied in CAMEL measure (capital adequacy, asset quality, management, earnings ability and liquidity) rather than the banks themselves, where CAMEL measure is proposed by the regulators to evaluate bank operation soundness. The result of this paper can be used by banks to evaluate how the mergers and acquisitions would impact their financial ratios, thus the banks can make better decisions on acquiring and plan for the adverse impact. For instance, the result shows that post mergers and acquisitions the non-performing loan would increase and the return on equity ratio would decrease for the acquiring banks. Therefore when a bank plans to acquire another bank, it can determine whether to acquire given these adverse impacts, and make plans accordingly if acquiring. The result of this paper can also be used by regulators when they review the acquisition applications to evaluate what would happen to the acquiring banks in terms of financial ratios implied by CAMEL measure.

The contribution of this paper is four fold. First, it enriches the banking mergers and acquisitions research literature by providing more empirical evidence on the performance impact of merger activity. The CAMEL measure includes five categories which are evaluated by banking regulators to determine the health of banks. This paper selects variables from each one of the five categories for analysis, thus it can deepen the understanding of the merger and acquisition effects. The results show that not all the financial ratios have been statistically significantly impacted by mergers and acquisitions. Equity ratio, commercial and industrial loan ratio, delinquent assets ratio, non-performing assets ratio and return on equity ratio have been statistically significantly impacted by mergers and acquisitions for the acquiring banks.

Second, this paper leverages average treatment effect on treated technique developed by Callaway and Sant'Anna (2019) [10] and applies it to see the group time average treatment effects post merger and acquisition events. The groups are differentiated by the year of the merger and acquisition events, and the times refer to the different time periods collapsed post merger and acquisition events. The technique combines the events study with the difference-in-difference method, and it provides a comprehensive view to see the average post merger and acquisition impacts considering the group and time differences. The research results provide the evidence that there are mostly consistent merger and acquisition effects on different groups with only small variations on the magnitude of the impact.

Third, this paper uses the quantile difference-in-difference effect analysis technique developed by Callaway and Li (2019) [9] to see the post merger and acquisition impact, considering the impact may change depending on the acquiring bank's performance distribution prior the merger and acquisition. The research result provides the evidence that there are variations of the merger and acquisition effects between the acquiring banks locating in the higher end and the acquiring banks locating in the lower tail of the investigated performance measure distribution. Sometimes this variation is significant enough to make the post acquisition impacts to be of two opposite directions, such as for equity ratio.

Last, the performance impact analysis has been conducted on different stages in an economic cycle. In particular, the data are segmented into pre-credit crisis, during-credit crisis and post-credit crisis periods, and the performance measures are investigated for all the three time periods. This partitioning allows for distinguishing bank behavior during different phases of the business cycle. Equity ratio, commercial and industrial loan ratio, delinquent assets ratio, non-performing assets ratio and return on equity ratio show significant impact from mergers and acquisitions for all the three time periods across the economic cycles. Four out of these five ratios show consistent impact in terms of the direction across the three time periods respectively, while equity ratio shows two directions of impact across the three time periods (equity ratio increases after mergers and acquisitions in the pre-credit crisis stage and during-credit crisis stage, but it decreases after mergers and acquisitions in the post-credit crisis stage). In addition to these five ratios, cash ratio exhibits significant impact post mergers and acquisitions mostly in the during-credit crisis stage.

2.2 Literature Review

DeYoung et al (2009) [15] gave a literature review on the post 2000s researches of financial institutions mergers and acquisitions. There are several research strands which get wide attention among the existing literature. Banks participate in mergers and acquisitions on the acquiring side to realize different goals. Hence as one important research strand, the study on the post merger performance for the acquiring banks can shed light on whether the performance moves in a consistent way as ex ante expectation. The performance measures in center can come from firm's financial statements such as different accounting ratios and efficiency frontiers, or stock market price movement for the banks which are publicly traded. For instance, using the data of bank mergers of the 1990s, Berger (1998) [6] found that on average bank mergers increase profit efficiency relative to other banks, but the cost efficiency effect is immaterial . He also found that the efficiency gains are much more pronounced when the participating banks are relatively inefficient. As another example, Knapp et al (2005) [26] analyzed 80 mergers of material bank holding companies from late 1980s and 1990s and examined both financial performance and stock price reactions to these mergers. He found that post mergers financial performance showed weakness in terms of declines on overall profitability relative to industry average. He also showed insignificant cumulative abnormal return on stock price in reactions to merger announcement and even negative median stock price return.

Other research focus on manager motive that affect their personal position or pay, but may not be related to firm profitability. For instance, managers who have their pay linked to firm size or growth tend to initiate bank acquisitions to increase size and their compensations. Anderson et al (2004) [4] investigated how mergers and acquisitions affect the managerial compensation in the acquiring banks. They used a sample of 97 mergers between billion-dollar banks in the 1990s and found significant average increase in CEO compensation post mergers and acquisitions.

As banking industry is important for the health of the whole economy, hence there are other post acquisition outcomes which draw researchers' interests. These outcomes focus on the impact on consumers or companies which conduct business with banks as borrowers. For example, Jagtiani et al (2016) [25] asked how community bank mergers impact small business lending. Their results indicated that mergers involving community bank targets didn't adversely impact small business lending, and thus they didn't significantly affect the credit size received by small business companies.

There are extant research on post mergers and acquisitions banking performance from both US and other geographies. Kwan and Wilcox (2002) [29] found that there would be cost reductions for acquiring banks analyzing the mergers of U.S. banks which happened during the 1990s. Knapp et al (2006) [27] provided more evidence on that mergers and acquisitions would bring profit gains during a period post mergers. Hagendorff et al (2009) [19] found that U.S. acquiring banks hadn't generated revenue improvement because costs increased for U.S. bank mergers between 1996 and 2004. For banking mergers and acquisitions outside U.S. market, there are also many research which focus on how the acquisitions affect the acquiring banks post acquisition performance. Huizinga et al (2001) [23] found that cost efficiency improved and profit efficiency gained slightly with analysis of 52 European bank mergers and acquisitions which happened between 1994 and 1998. Du and Sim (2016) [16] studied the emerging markets mergers and acquisitions effects, using six emerging countries including China, India, Indonesia, Malaysia, Russia and Thailand between 2002 and 2009. They found improved efficiency for target banks while not significant improved efficiency for acquiring banks.

The focal topic of this paper is the impact of bank acquisitions on the banks that acquire. This paper uses two methodologies in extended difference-in-difference techniques to see the post merger impact. The first technique is proposed by Callaway and Sant'Anna (2019) [10] which is to estimate the average group time difference-in-difference impact post treatment events. Standard difference-in-difference has two time periods and two groups. The two time periods include one pre-treatment time period and one post-treatment time period, while the two groups are differentiated by whether the entity receives the treatment or not. It also assumes the treatment group receives the treatment at the same time. This simple setup is easy to interpret and gives insights for the treatment effect in an intuitive way. However, the simple setup has limitations in more complicated cases. Callaway and Sant'Anna (2019) [10] extend the standard difference-in-difference setup to multiple time periods and allow for variation in treatment timing. Their approach estimation made an important assumption that the parallel trends hold potentially only after conditioning on observed covariates, so that it permits broader application of the difference-in-difference. This paper uses this methodology to derive the banking merger and acquisition effects for acquiring banks with different acquisition timings, and it also gives insights on how the effects evolve over time in the post acquisition time periods.

The second technique used in this paper is proposed by Callaway and Li (2019) [9] which is to estimate the quantile treatment effects on the treated post treatment events. The group time difference-in-difference methodology focuses on the impact from one measure dimension, namely the average effect. In contrast, the method which was proposed by Callaway and Li (2019) [9] of quantile treatment effect on treated research uses distributional difference-in-difference assumption instead of the mean difference-in-difference assumption, thus this method can be used to understand extended treatment (mergers and acquisitions) effects on the entities (acquiring banks) with the value in interest (performance measures in terms of financial ratios) in the lower tail or higher tail of its distribution.

2.3 Methodology

This paper uses two methodologies in extended difference-in-difference techniques to see the post merger impact. In the first methodology, the acquiring banks are categorized to different groups based on the timing of the acquisitions. When a bank takes over other banks in more than one time period during the observation time, then the bank is grouped to the time period which sees the largest asset growth for that particular bank. This treatment can allow the analysis to focus on the most influential mergers and acquisitions as acquiring targets with bigger size is more challenging and would impact the acquiring bank more significantly. The acquiring bank's performance post merger in terms of the financial ratios implied by CAMEL measure is analyzed using difference-in-difference method with multiple time periods proposed by Callaway and Sant'Anna (2019) [10] to see the average group time impact from the mergers and acquisitions. The analysis from first methodology gives insights on the average impact from mergers and acquisitions. In the second methodology, this paper follows the approach proposed by Callaway and Li (2019) [9] to estimate quantile difference-in-difference treatment effects on the acquiring banks, thus it can provide a view to see how the merger and acquisition impacts on each of the performance measures contingent on the corresponding measure's location in its distribution prior to the treatment. Using these two extended difference-in-difference techniques can give more comprehensive insights on the mergers and acquisitions impacts.

2.3.1 Group Time Difference-In-Difference Analysis

The setup of this method is applied in banking merger effects analysis, and it starts with the extension of the standard difference-in-difference setup. Assume there are T time periods and denote a specific time period by t where $t = 1, ..., T$. Here T is a number larger than 2. In this method, no bank acquires in period 1. A bank is considered to acquire if it acquires at least one bank during the observation period, and the acquisition results in the biggest asset growth for the acquiring bank among all the acquisitions during the time period analyzed. Denote D_t as a binary variable with value of 1 representing this bank takes acquisition in period t and zero otherwise. In addition, define G_g to be a binary variable with value of 1 representing this bank takes acquisition in period g. Here a bank can acquire at any time period from period 2 to period T. The acquiring banks are segmented to different groups based on acquisition timing g. Besides the banks which acquire, there is another controlling group. The banks in the controlling group have never acquired any banks during the time period analyzed. At last, denote $Y_t(1)$ and $Y_t(0)$ as the potential outcomes at time t when the bank acquires and doesn't acquire respectively. In the case of more than two time periods and there is variation in the treatment timing, Callaway and Sant'Anna (2019) [10] developed a method to estimate the average treatment effect for the acquiring banks which belong to a specific group g in a specific time period t as:

$$ATT(g,t) = E[Y_t(1) - Y_t(0)|G_g = 1] \tag{2.3.1}$$

As one bank cannot be observed to both acquire and not acquire at the same time t, hence Y_t is either 1 or 0. Thus solving the estimation on the unobserved feature from one of the $Y_t(1)$ and $Y_t(0)$ is the key research problem in the difference-in-difference literature. Callaway and Sant'Anna (2019) [10] solved the estimation based on the important conditional parallel trends assumption. The conditional parallel trends assumption states that, for all $t = 2, ..., T$, $g = 2, ..., T$, such that $g \leq t$, the below equation holds:

$$E[Y_t(0) - Y_{t-1}(0)|X, G_g = 1] = E[Y_t(0) - Y_{t-1}(0)|X, C = 1] \tag{2.3.2}$$

Here X represents a vector of the independent variables which impact the outcomes, and the parallel trends hold conditional on controlling these variables. This paper considers three independent variables (bank age, whether the bank has a foreign branch and the local market banking competition environment represented by HHI) to be controlled to analyze the effects. The potential outcome of not taking acquisitions for the acquiring banks which acquire at time period g is not observable, but the outcome of not taking acquisitions for the banks which are in the controlling group is observable. When the assumptions hold, the potential outcome of not taking acquisitions for the acquiring bank group g can be estimated, thus the average effect on the acquiring bank group g can be estimated. Furthermore, as this equation holds in dynamic time periods, namely $t = 2, ..., T$, hence dynamic average treatment effect on treated can be estimated for different time periods post mergers.

2.3.2 Quantile Difference-In-Difference Analysis

This paper also applies the quantile difference-in-difference method developed by Callaway and Li (2019) [9] to see the quantile treatment effect on different financial measures post mergers and acquisitions for the acquiring bank. Take the financial ratio of return on equity for an instance, using the method developed by Callaway and Li (2019) [9], I analyzed the effect when the return on equity of the acquiring bank is in the lower tail such as 10th percentile, or in the higher tail such as 90th percentile among all the acquiring banks.

To understand how the method works for bank acquisitions in a formal setup, assume there are three time periods, $t-2$, $t-1$ and t. All the acquiring banks only acquire at the final time period t. There is a binary treatment D_t. When $D_t = 1$, it means the bank acquires at time t, while $D_t = 0$ means the bank doesn't acquire at time t. For each bank, three outcomes are observed along the three time periods, denote them as Y_{t-2}, Y_{t-1} and Y_t. Each bank at the final time point t has two potential outcomes, which are the treated state (the bank takes acquisition) denoted as Y_{1t}, and untreated state (the bank doesn't take acquisition) denoted as Y_{0t}. For each bank at a specific time point, only one of the two potential outcomes can be observed as an bank cannot fall in both states at the same time. In the first two time periods no banks acquire, hence the observed outcome for both treated group and untreated group are the outcomes when there is no treatment (no acquisitions), which are $Y_{0(t-1)}$ and $Y_{0(t-2)}$ for the two time periods and for both groups (the treated group $D_t = 1$ and the untreated group D_t =0). A typical treatment effect is the difference between Y_{1t} and Y_{0t}. Under the quantile treatment effect on treated setup, quantile treatment effect on the treated (QTT) is defined as:

$$QTT(\tau) = F^{-1}_{Y_{1t}|D_t=1}(\tau) - F^{-1}_{Y_{0t}|D_t=1}(\tau) \tag{2.3.3}$$

In this equation, $F_{Y_{1t}|D_t=1}$ and $F_{Y_{0t}|D_t=1}$ denote the cumulative distributions of Y_{1t} and Y_{0t} respectively conditional on being in the group of treatment. τ is a quantile measure with value between 0 and 1, and τ-quantile y_τ of a random variable Y is defined as below:

$$y_\tau = F_Y^{-1}(\tau) := inf\{y : F_Y(y) \geq \tau\} \tag{2.3.4}$$

To estimate the quantile treatment effect on the treated, the following three assumptions are taken from Callaway and Li (2019) [9]. First, I assume Copula Stability, which requires that the dependence between $(\Delta Y_{0t}|D_t = 1)$ and $(Y_{0(t-1)}|D_t = 1)$ is the same as the dependence between $(\Delta Y_{0(t-1)}|D_t = 1)$ and $(Y_{0(t-2)}|D_t = 1)$. Second, I assume the support of the change in untreated outcomes for the untreated group in period t of $(\Delta Y_t|D_t = 0)$, the support of the change in the untreated outcomes for the treated group in period $t-1$ of $(\Delta Y_{t-1}|D_t = 1)$, the support of the untreated outcomes for the treated group at period $t-1$ of $(Y_{t-1}|D_t = 1)$ and the support of the untreated outcomes for the treated group at period $t-2$ of $(Y_{t-2}|D_t = 1)$ are compact and continuously distributed on their support with densities that are bounded from above and bounded away from 0. Third, I assume the observed data are independently and identically distributed. The distribution of $(Y_{0t}|D_t = 1)$ can be estimated as:

$$
\begin{aligned}
&F_{Y_{0t}|D_t=1}(y) \\
&= E[I\{F^{-1}_{\Delta Y_t|D_t=0}(F_{\Delta Y_{t-1}|D_t=1}(\Delta Y_{t-1})) \leq y - F^{-1}_{Y_{t-1}|D_t=1}(F_{Y_{t-2}|D_t=1}(Y_{t-2}))\}|D_t = 1]
\end{aligned}
\tag{2.3.5}
$$

The distribution of $(Y_{1t}|D_t = 1)$ is observed for the acquiring group, combined with the distribution of $(Y_{0t}|D_t = 1)$ estimated in equation (5), the quantile treatment effect on the treated can be estimated using equation (3).

2.4 Data and Specification of Variables

2.4.1 Data Source and Summary

In this paper, the data is collected from two sources. First, U.S. banking mergers and acquisitions data is acquired from National Information Center (NIC) maintained by Federal Reserve Board. The data gives details of the information about the two sides in the mergers and acquisitions deals, including the names and banking types for both the acquiring banks and target banks. It also provides deal information like merger date and merger outcome such as whether the target bank stops existing as an independent bank or not. This paper narrows the time period of the mergers and acquisitions down to between 2003 and 2014. This data curtailment, which doesn't extend to the most recent periods or include any data prior to 2003, is for the consideration of balancing the time spent on data collection and achieving meaningful implication in the study. The time periods include one economic cycle and thus can provide flexibility to analyze the performance measures in pre-credit, during-credit and post-credit crisis time periods. This paper only focuses on the merger outcome that the target banks stop existing and transform all the assets to the acquiring banks post-merger, hence it excludes other forms of the acquisition outcomes.

The second data source is from FDIC reports, which provides two sets of reports to be used in this paper. First, the call reports provide a source to derive US bank level financial ratios which represent banks' performance. They also provide the foreign deposits data, which is the instrument for whether each filing bank has foreign branches. The data also ranges from 2003 to 2014. Second, the all reports provide data on each bank's age and county of headquarter. After getting headquarter-based county information for each bank, I calculated the HHI index for each county based on all the banks in the county using their deposits value. The HHI index is an indicator of bank concentration, with a larger value indicating higher concentration and lower level of local competition. I use this index as one of my three independent variables. The data from the two sets of FDIC reports are merged together to provide the three controlled variables (bank age, indicator of whether the bank has foreign deposits and HHI index), as well as the bank level financial ratios which represent banks' performance measures.

The data sets from the two data sources are merged together by taking all the banks existing in FDIC reports in different time periods as base and then assigning acquiring flag to each of the acquiring banks at the merging time periods. Some of mergers and acquisitions are dropped because there is no corresponding FDIC report information for the acquiring banks. Although it doesn't reflect the analysis on all the banks which acquire, the banks which file FDIC reports are in center and can represent the banks operating in U.S.. The combined dataset has all the time series of selected financial ratios for all the banks existing in FDIC call reports, as well as acquisition information for each acquiring bank at the acquisition time point.

The combined dataset is analyzed and Table 1 shows summary statistics of the three controlled variables (bank age, whether the bank has foreign deposits and HHI index) in each year differentiated by the acquiring group and non-acquiring group. The bank age is in the form of log transformation. The indicator of whether the bank has a foreign branch is a binary dummy variable with value of 1 representing the bank has foreign deposits, and 0 otherwise. The HHI index represents the local market banking competition environment faced by the bank.

Table 2.1: Group Summary Statistics of Three Controlled Variables Over Time

Year	Acq.	MeanAge	SdAge	MeanFor.	SdFor.	MeanHHI	SdHHI
2003	0	3.83	1.11	0.02	0.12	3210	2397
2003	1	3.91	1.06	0.08	0.28	3793	2575
2004	0	3.85	1.09	0.02	0.13	3242	2428
2004	1	3.92	0.98	0.07	0.25	3629	2630
2005	0	3.86	1.07	0.01	0.12	3337	2457
2005	1	4.14	0.88	0.08	0.28	3710	2533
2006	0	3.87	1.07	0.02	0.13	3420	2474
2006	1	4.00	0.95	0.08	0.28	4055	2717
2007	0	3.86	1.09	0.02	0.12	3410	2496
2007	1	4.09	0.93	0.07	0.26	4081	2765
2008	0	3.83	1.13	0.03	0.16	3450	2532
2008	1	4.10	0.87	0.09	0.29	3896	2697
2009	0	3.81	1.15	0.03	0.18	3463	2538
2009	1	4.01	1.04	0.13	0.34	3656	2626
2010	0	3.83	1.13	0.02	0.15	3436	2527
2010	1	3.83	1.08	0.08	0.27	3617	2535
2011	0	3.89	1.08	0.02	0.14	3533	2558
2011	1	3.76	1.08	0.06	0.23	3793	2391
2012	0	3.94	1.02	0.02	0.14	3675	2586
2012	1	3.89	1.11	0.06	0.24	3900	2623
2013	0	4.00	0.97	0.01	0.12	3730	2642
2013	1	3.90	1.01	0.06	0.24	4040	2740

Table 2.1: (continued)

Year	Acq.	MeanAge	SdAge	MeanFor.	SdFor.	MeanHHI	SdHHI
2014	0	4.06	0.91	0.01	0.12	3674	2617
2014	1	3.92	0.99	0.02	0.15	4083	2774

From Table 2.1, it can be observed that the average age measure for the acquiring banks is around 4, and this average age measure doesn't quite vary over the time. In addition, there is no big difference on the average age measure between the acquiring banks and non-acquiring banks in each year. In terms of whether a bank has foreign deposits, it shows that the acquiring banks have significant larger proportion of banks with foreign deposits than the non-acquiring banks in each year. For instance, 8% of the banks which acquired in 2005 have foreign branches, while only 1% of the banks which didn't acquire in 2005 have foreign branches. In terms of local market HHI index, it shows that the acquiring banks have larger average HHI index than the non-acquiring banks in each year. The higher HHI index is, the more concentrated the local market is. Both acquiring banks and non-acquiring banks have average HHI index of over 3000 in each year, which evidences that the local markets are concentrated for the banking industry in general.

2.4.2 Specification of Target Variables

Bank regulators, including the Fed, use what they call CAMEL, to estimate bank performance and health. CAMEL is a set of five bank variables, where 'C' reflects capital adequacy, 'A' reflects Asset Quality, 'M' reflects management quality, 'E' reflects earning ability, and 'L' reflects liquidity. In this paper, I also looked into the financial ratios implied in these 5 categories of CAMEL measure, to see how the mergers and acquisitions impact these financial ratios for acquiring banks. In terms of capital adequacy, this paper uses equity ratio. In term of asset quality, this paper uses six asset ratios, four ratios of which represent the asset allocations to different loans while the other two ratios represent the bad asset components of the bank. In terms of management quality, this paper uses two ratios, one of which represents the non-operating expense while the other ratio is profit per employee. In terms of earning ability, this paper uses two ratios which are return on equity and operating profit ratio. For liquidity, this paper uses the most liquid asset ratio which is the cash rate. Table 2.2 shows the definitions of selected target performance measures of financial ratios implied by CAMEL.

Table 2.2: Financial Ratios and Definitions

Name	Definition
EquityRatio	total equity / total assets
TotalLoan	total loans/total assets
ReLoan	real estate loans/total loans
CniLoan	commercial and industrial loans/total loans
OtherRe	other real estate owned / total assets
Delinquent	past due 30 days through 89 days and still accruing/total assets
NonPerforming	nonperforming loans/total assets
NonOperatingExp	noninterest expense / total assets
ProfitPerEmployee	net profit / number of employees
ROE	net after tax income / total equity
OperatingProfit	(net interest income - operating expenses)/total interest income
CashRate	(federal funds purchased and securities purchased under agreements to resell - fed funds sold and securities sold under agreements to repurchase) /total assets

The summary statistics for each financial ratio of the acquiring banks at the time of acquisition is shown in Table 2.3, which covers the whole observable time periods which starts from 2003 to 2014 at annual frequency. All of the financial measures presented in Table 2.3 are in terms of percentage unit except profit per employee which is in terms of dollar value.

Table 2.3: Acquiring Banks Financial Ratios Summary Statistics

Target	Mean	St. Dev.	Min	Max
EquityRatio	10.9	3.2	2.1	60.5
TotalLoan	67.0	12.0	1.7	99.4
ReLoan	70.7	16.3	0	100
CniLoan	11.5	10.1	0	82.5
OtherRe	0.4	0.7	0	16.6
Delinquent	0.7	0.6	0	6.1
NonPerforming	1.1	1.5	0	17.6
NonOperatingExp	7.0	3.3	0.5	64.8
ProfitPerEmployee	179	4,249	−2,832	225,550
ROE	19.5	43.9	−1245.1	254.3
OperatingProfit	7.0	74.8	−3424	68.8
CashRate	−1.0	5.0	−75.1	49.5

The summary statistics for all the banks in the periods without mergers and acquisitions are also investigated and can be found in appendix. The takeaway is that most ratios show similar means between the acquiring banks in the acquisition time periods and the otherwise, except a few ratios show differences such as commercial and industrial loan ratio, operating profit ratio and cash rate. However, the direct comparison is too simplified to get more robust conclusion on the mergers and acquisitions impact. This paper uses the two methodologies detailed in the methodology section and the results ensue below.

2.5 Estimation Results

This paper uses both group time difference-in-difference analysis and quantile difference-in-difference analysis to estimate the US banking mergers and acquisitions impact on the acquiring banks. Both estimations are conducted on the panel data with annual interval. The quarterly interval data was also considered for analysis at first but it was excluded from final decision as it may incur additional seasonality consideration while using annual data can ease it. Under the case that when an acquiring bank acquires banks for more than one time during the time period segment, for example when the bank is on strategy to expand in order to open business in new geographic areas or gain more market shares in local markets, the analysis is focused on the consolidated mergers which cause largest year over year asset growth rate for that acquiring bank and treats the bank acquires in that specific year. The selection of the largest asset acquisitions to the acquiring banks is because they may strike most challenge and affect the post acquisition performance most. The analysis is conducted for three different time period segments, namely pre-credit crisis, during-credit crisis and post-credit crisis periods. Hence this paper is able to provide the insights of whether the overall economic environment affects the post merger performance.

2.5.1 Group Time Difference-In-Difference Analysis Estimation Results

The data is segmented into the pre-credit crisis stage, during-credit crisis stage and post-credit crisis stage. For each stage, this paper analyzes four years of panel data. The estimation equation is conditional on three controlled variables: (1) the bank's age; (2) whether the bank has foreign branches; and (3) the local market HHI index for the bank. The group time difference-in-difference impact of mergers and acquisitions on each of the target performance measures is estimated, conditional on the three controlled variables.

2.5.1.1 Pre-Credit Crisis Results

In the pre-credit crisis stage, the data is narrowed down to the time periods between 2003 and 2006. The data is in the panel structure. The Group label is created based on which year the acquiring bank realized largest asset growth through acquisition between 2003 and 2006. For instance, if an acquiring bank acquires the largest assets in 2004, it is regarded as Group 2004. All the acquiring banks belonging to Group 2003 (first year of the panel) were dropped from the panel data, thus the first year of the panel are all observed untreated to provided components to estimate the potential unobserved non-treated outcome for the treated group. Table 2.4 shows the group time impact estimation (first row) for each of the target performance measures in terms of financial ratios and its corresponding standard deviation (second row).

In terms of the capital adequacy measure, all the groups show statistically significant enhanced equity ratios post merger and acquisition. For example, the acquiring banks of Group 2005, which achieved largest acquisition in terms of largest asset growth rate in time period 2005, show the equity ratio increases by an average of 68 basis points in 2005 and 75 basis points in 2006. The result provides the evidence that the acquiring banks increase capital ratio post acquisitions.

In terms of the asset measures, among the four asset ratios of different loans, not all the measures show statistically significant changes post mergers. For instance, the total loan ratio and other real estate loan ratio don't display statistically significant changes post mergers for the acquiring banks. Real estate loan ratio is observed to have statistically significant positive change post mergers for Group 2005 over time, and no changes on this ratio are observed for Group 2004 and Group 2006. Commercial and industrial loan ratio is observed to increase post mergers for all the three acquiring groups over time except for group 2005 in time period 2005, which implies that post

Table 2.4: Financial Ratios Results - Pre-Credit Crisis

FinancialRatio	Group2004			Group2005		Group2006
	2004	2005	2006	2005	2006	2006
EquityRatio	0.34	0.58	0.64	0.68	0.75	0.62
	(0.12)	(0.17)	(0.20)	(0.19)	(0.21)	(0.16)
TotalLoan	0.31	0.61	0.87	0.08	-0.31	-0.27
	(0.39)	(0.53)	(0.60)	(0.56)	(0.68)	(0.39)
ReLoan	-0.30	-0.38	-0.47	1.01	1.38	0.10
	(0.34)	(0.53)	(0.60)	(0.38)	(0.48)	(0.34)
CniLoan	1.86	2.21	2.17	0.54	1.15	1.34
	(0.51)	(0.60)	(0.59)	(0.38)	(0.51)	(0.48)
OtherRe	-0.00	-0.02	-0.03	-0.00	0.00	0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Delinquent	0.02	-0.02	0.00	0.05	0.07	0.04
	(0.03)	(0.04)	(0.04)	(0.02)	(0.03)	(0.02)
NonPerforming	-0.01	-0.00	0.00	0.06	0.09	0.01
	(0.03)	(0.04)	(0.05)	(0.02)	(0.03)	(0.03)
NonOperatingExp	-0.26	-0.03	-0.10	-0.16	-0.16	-0.04
	(0.10)	(0.12)	(0.17)	(0.09)	(0.14)	(0.09)
ProfitPerEmployee	-32	248	396	231	378	102
	(50)	(195)	(296)	(181)	(285)	(91)
ROE	-3.32	-1.13	-0.35	-4.30	-2.69	-3.08
	(1.10)	(1.29)	(1.63)	(0.81)	(1.24)	(0.95)
OperatingProfit	-0.86	-1.23	-1.21	-1.74	-1.09	-0.74
	(0.68)	(1.17)	(1.53)	(0.87)	(1.04)	(0.80)
CashRate	0.01	0.04	-0.34	0.34	-0.04	0.05
	(0.24)	(0.29)	(0.33)	(0.20)	(0.27)	(0.24)

mergers all the acquiring banks have statistically significant higher commercial and industrial loan component. For the two bad assets ratios, both delinquent asset ratio and non-performing asset ratio show statistically significant positive change for group 2005 in time periods 2005 and 2006. In addition, the delinquent asset ratio shows statistically significant positive change for group 2006 in time period 2006.

In terms of management quality, there are no statistically significant changes post mergers on both non-operating expense ratio and profit per employee for all the groups and times, except that group 2004 in time period 2004 displays negative change on the non-operating expense ratio. Overall, it provides evidence that the mergers and acquisitions don't affect the management quality significantly. It may be due to that management of an acquiring bank has no significant change post mergers, for instance, the important managers are mainly from the acquiring banks rather than the target banks and the management style is more affected by the acquiring banks rather than target banks. Hence the non-operating expense and profit per employee don't undergo much change.

In terms of the earning ability, there are no statistically significant changes on the operating profit ratio for all the acquiring groups in all the time periods. However, negative impacts from mergers on return on equity ratio are observed for all the groups in nearly all the periods post mergers, except for group 2004 in periods 2005 and 2006. The return on equity is a traditional profit measure and looked into by many stakeholders including shareholders and potential investors. The decrease of this ratio shows that post mergers the profit relative to equity decreases and it may not be attracted to the potential investors. The decrease in return on equity ratio may be also related to the increase in equity ratio.

In terms of the liquidity ratio, the acquisitions show no statistically significant impact on the acquiring banks for all the groups and time periods post acquisitions. The liquidity ratio is mostly determined by banks' strategy plan and is also subjected to regulatory requirement such as Basel accords. The result shows the acquisitions don't significantly affect the liquidity ratio in terms of cash ratio.

Figure 2.1 to Figure 2.6 present the graphs of the average impacts on the six financial ratios which display statistically significant changes post mergers for the acquiring banks in pre-credit crisis stage.

2.5.1.2 During-Credit Crisis Results

In the during-credit crisis stage, the data is restricted to the time periods between 2007 and 2010. The data is also in the panel structure. There are three acquiring bank groups, namely Group 2008, Group 2009 and Group 2010. Table 2.5 shows the estimation results of acquisition impacts on the three groups from each of the financial ratios representing performance measure in the during-credit crisis stage. All the impacts on the financial ratios presented in the table are in terms of percentage unit except profit per employee which is in terms of dollar value.

In terms of capital adequacy, the equity ratio is estimated to significantly increase for Group 2008 in all the time periods post mergers, while for all other groups the impacts are not statistically significant. It implies that although not always but overall the acquiring banks hold more equity ratio post mergers in the during-credit crisis stage.

The results of asset component ratios show that overall there are no statistically significant post acquisition impacts on real estate loan component and other real estate loan component. For total loan ratio, statistically significant negative impact on the Group 2010 in the time period 2010 is estimated while other groups don't show any significant changes. Acquisitions show statistically positive impact on the commercial and industrial loan ratio for Group 2008 in time period of 2008 and Group 2009 in time periods of 2009 and 2010, which is consistent with the results from the pre-credit crisis period. The two measures of bad asset ratios which represent asset quality

Figure 2.1: Equity Ratio Results - Pre-Credit Crisis

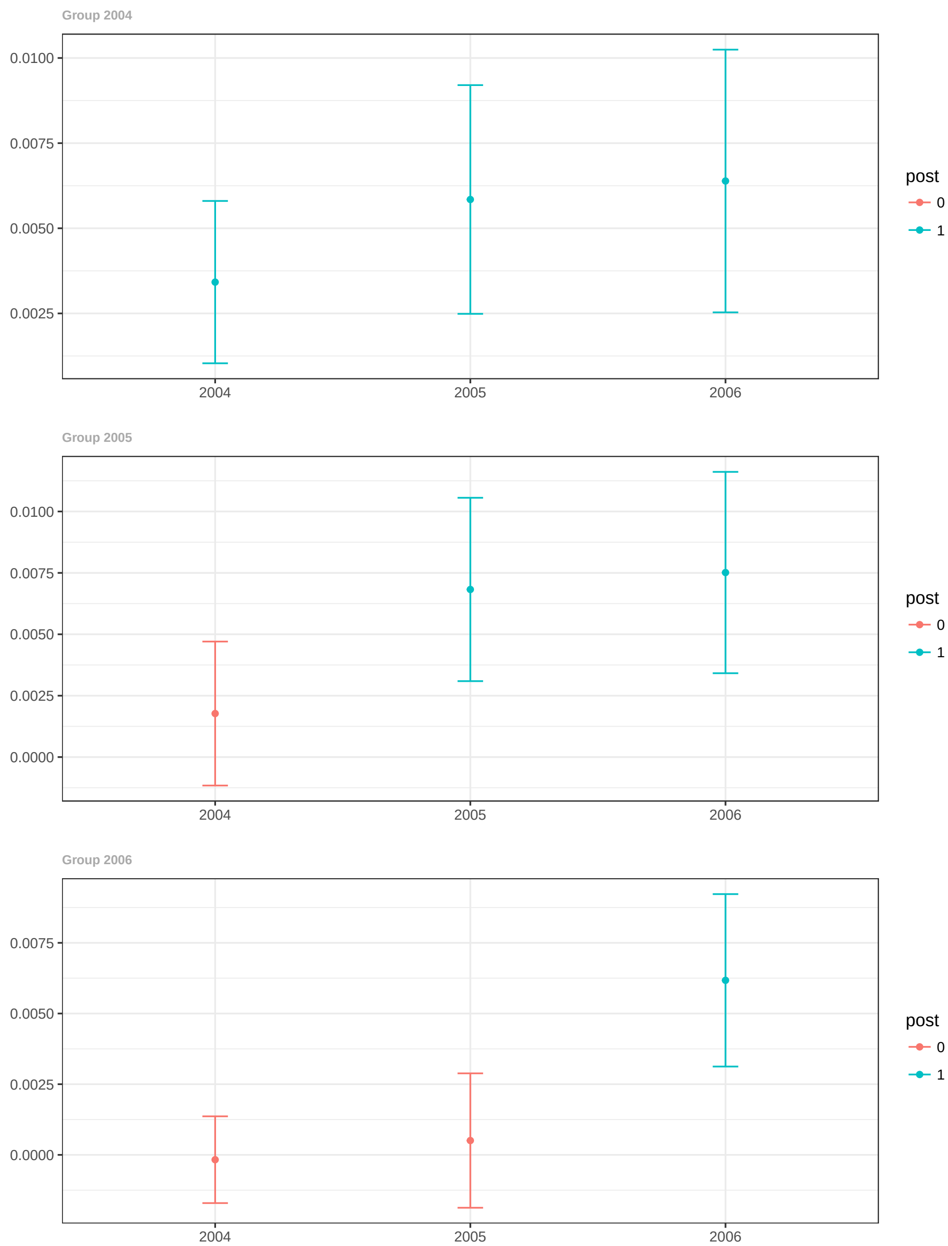


Figure 2.2: Real Estate Loan Ratio Results - Pre-Credit Crisis

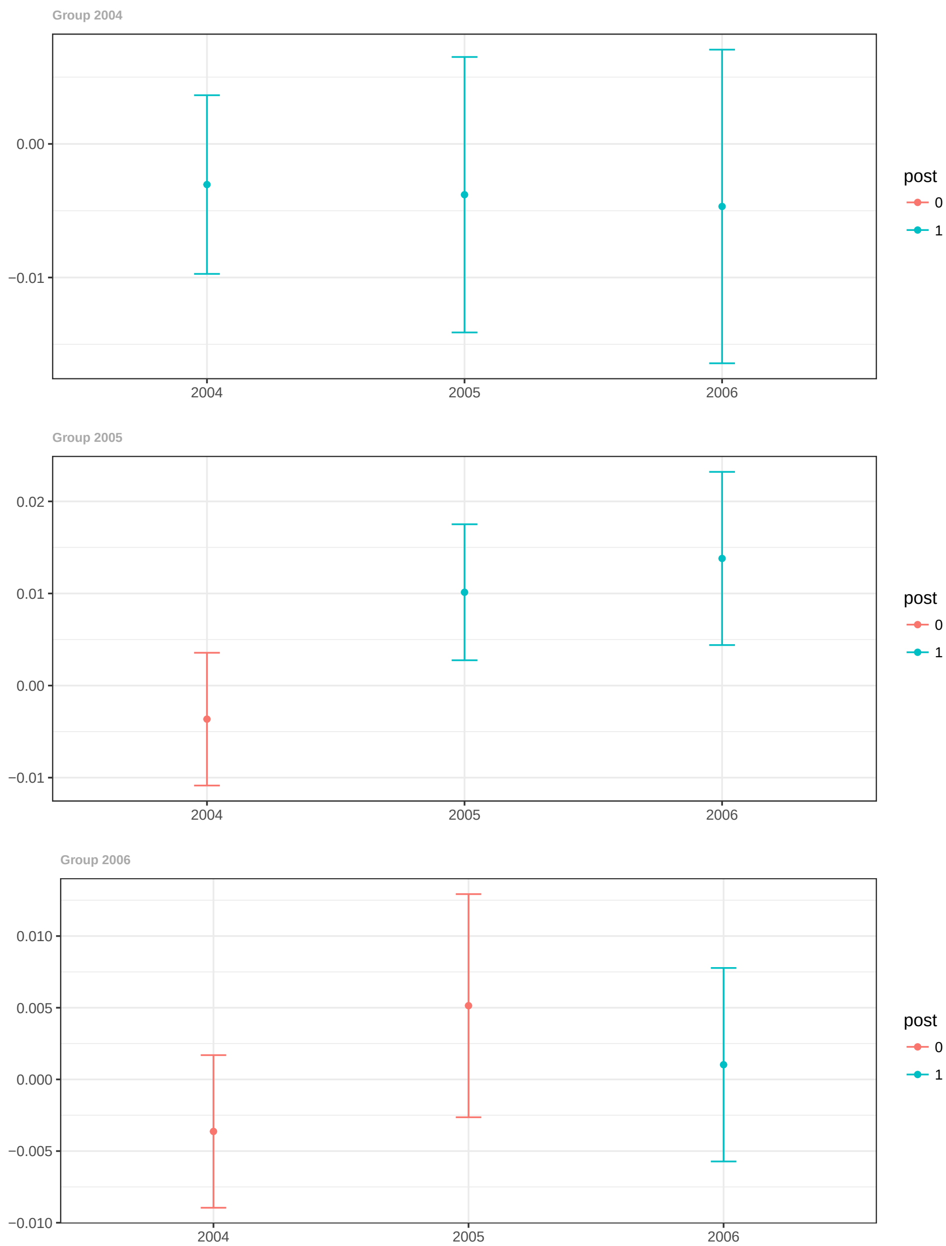


Figure 2.3: Commercial and Industrial Loan Results - Pre-Credit Crisis

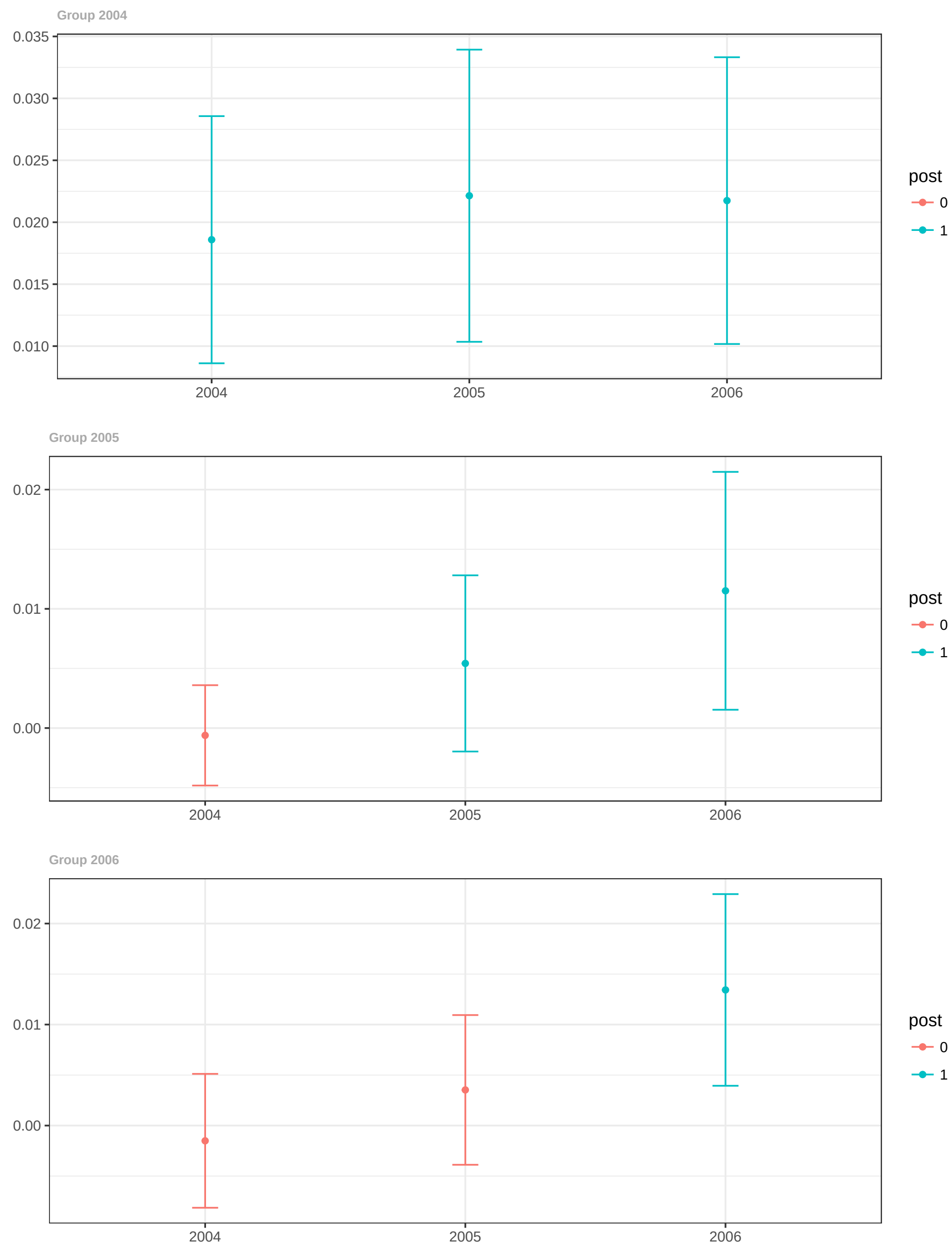


Figure 2.4: Delinquent Assets Results - Pre-Credit Crisis

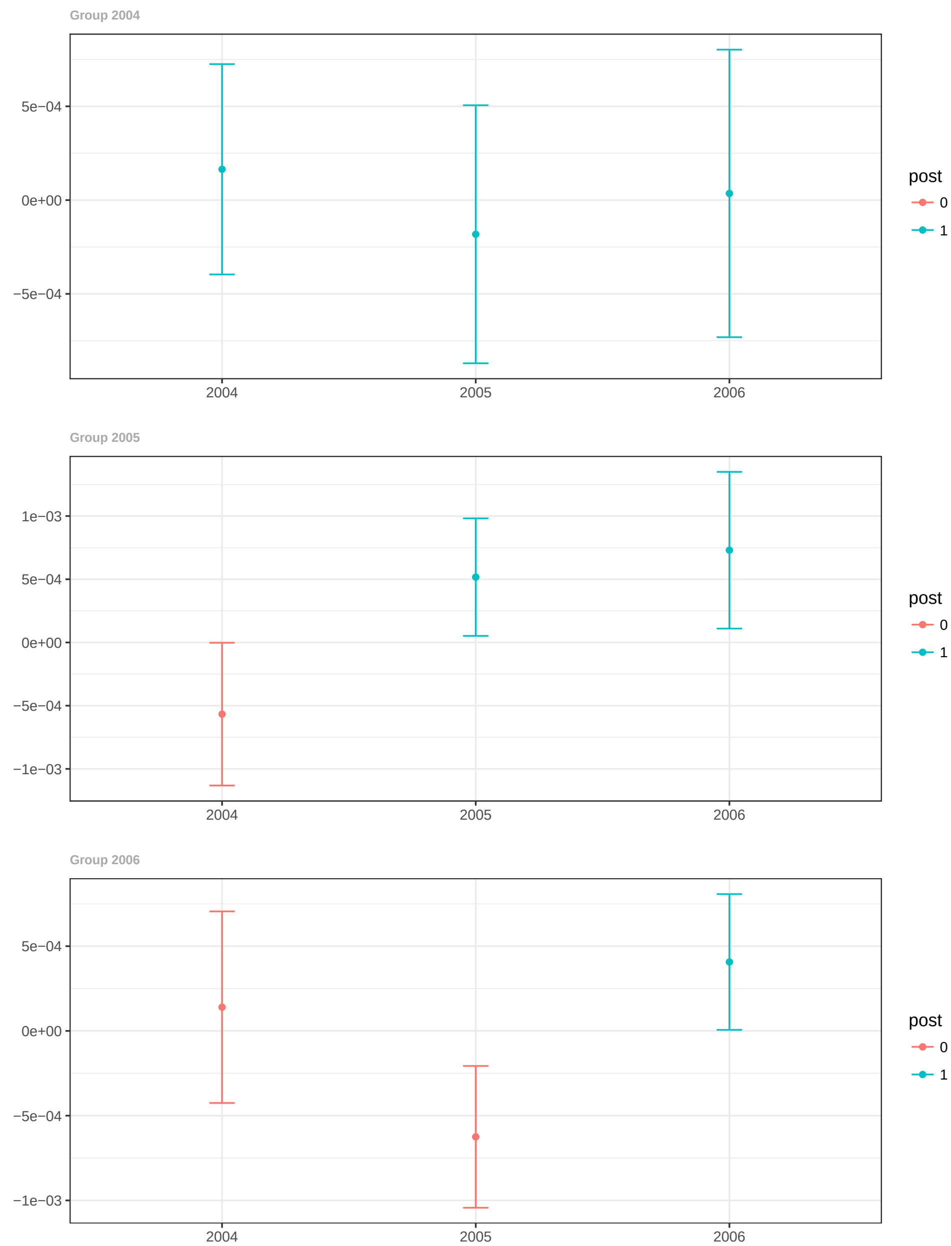


Figure 2.5: Non Performing Assets Results - Pre-Credit Crisis

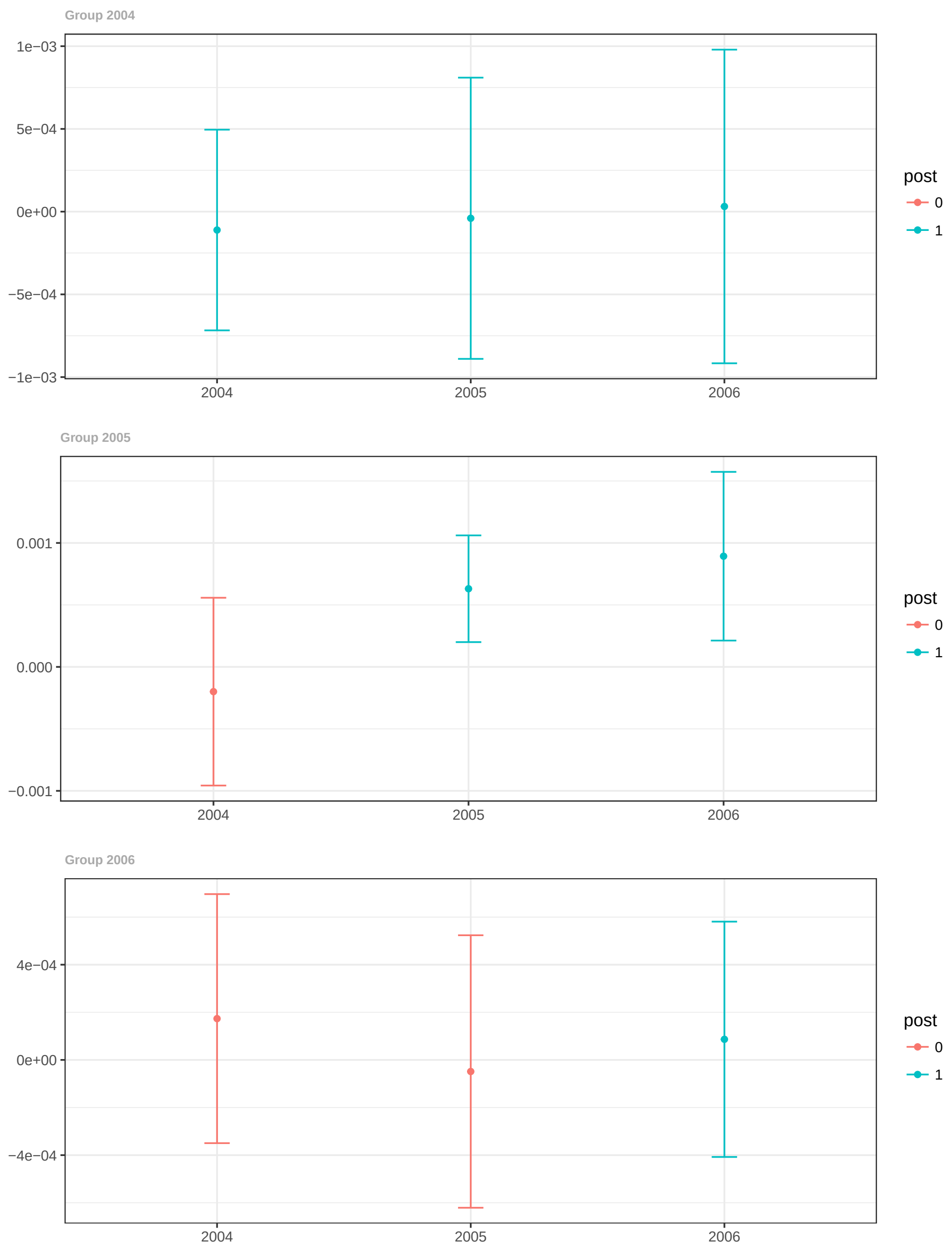


Figure 2.6: Return on Equity Results - Pre-Credit Crisis

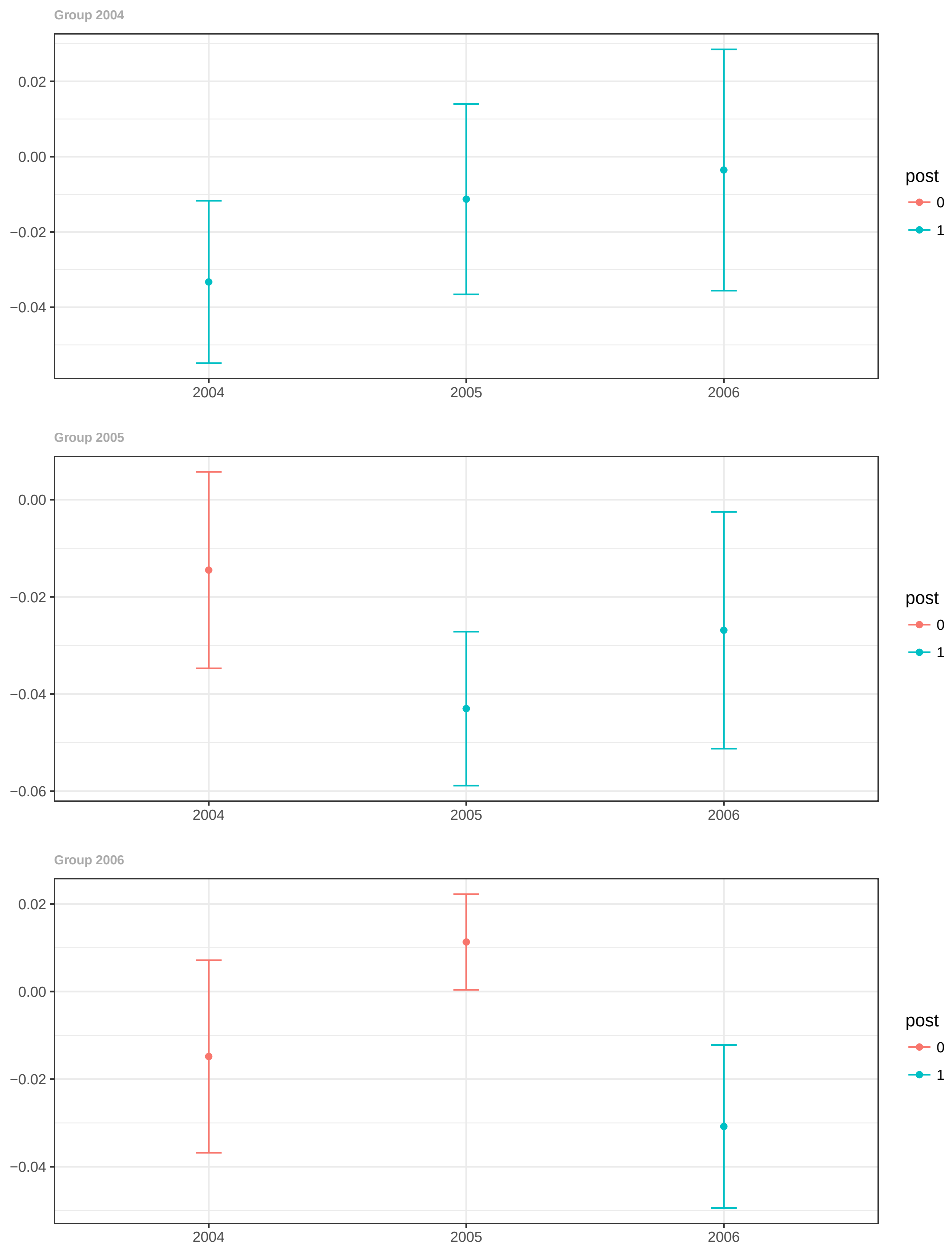


Table 2.5: Financial Ratios Results - During-Credit Crisis

FinancialRatio	Group2008			Group2009		Group2010
	2008	2009	2010	2009	2010	2010
EquityRatio	0.47	0.57	0.65	-0.07	-0.03	0.08
	(0.15)	(0.20)	(0.22)	(0.18)	(0.31)	(0.12)
TotalLoan	-0.04	0.21	0.28	-0.26	0.16	-0.99
	(0.38)	(0.60)	(0.69)	(0.48)	(0.77)	(0.42)
ReLoan	-0.12	-0.12	-0.26	0.40	0.75	-0.06
	(0.31)	(0.52)	(0.55)	(0.33)	(0.46)	(0.38)
CniLoan	0.98	0.82	0.74	0.94	1.12	-0.09
	(0.42)	(0.54)	(0.56)	(0.41)	(0.57)	(0.29)
OtherRe	0.01	0.02	-0.03	-0.03	0.01	0.06
	(0.03)	(0.05)	(0.07)	(0.04)	(0.07)	(0.06)
Delinquent	0.09	0.09	0.10	0.09	0.09	0.07
	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)
NonPerforming	0.09	0.36	0.42	0.38	0.52	0.59
	(0.07)	(0.14)	(0.17)	(0.11)	(0.19)	(0.16)
NonOperatingExp	0.36	0.85	0.11	-0.02	-0.29	0.05
	(0.21)	(0.22)	(0.17)	(0.27)	(0.45)	(0.17)
ProfitPerEmployee	-8	525	-164	-1775	-1437	-15
	(34)	(883)	(108)	(1759)	(1419)	(30)
ROE	-4.74	-15.10	24.62	-7.98	2.04	12.33
	(2.56)	(7.19)	(14.41)	(7.93)	(9.05)	(11.29)
OperatingProfit	-0.27	0.39	20.22	0.49	25.77	18.30
	(1.82)	(3.88)	(15.67)	(3.47)	(16.99)	(13.53)
CashRate	0.56	1.05	1.18	0.77	0.76	0.47
	(0.24)	(0.33)	(0.38)	(0.28)	(0.41)	(0.26)

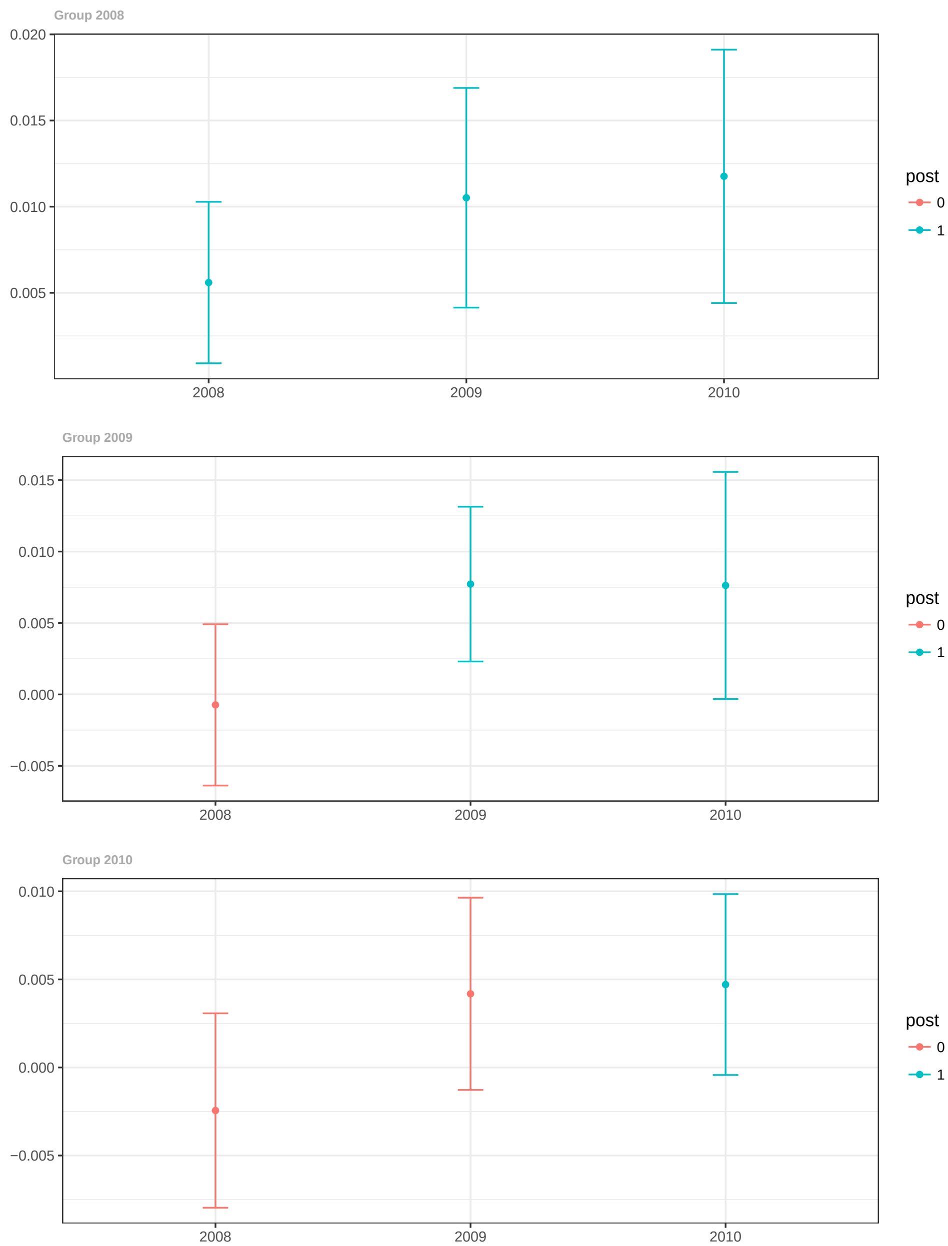
show statistically significant higher ratios post acquisitions for majority group time combinations in the during-credit crisis stage, which is also observed in the pre-credit crisis stage. It implies the acquisitions make acquiring banks' bad assets increase which may be due from the higher bad asset ratios of acquired banks, and this increase doesn't go away with times post acquisitions.

For the two management quality ratios, there are no statistically significant effects estimated for all the acquiring groups and times except the non-operating expense ratio for group 2008 in the period 2009 (positive change). It implies that during the credit crisis period, the management quality change is not one of the major impacts from the mergers and acquisitions.

For the two earning ratios, negative significant post acquisition impact is estimated for Group 2008 in the time period 2009 in terms of return on equity ratio, while there is no statistically significant post acquisition impact on operating profit ratio. Specifically the results show that post acquisitions the return on equity drops by 15% for Group 2008 in the time period 2009, which cannot support the motivation to realize return gain from mergers and acquisitions for acquiring banks during-credit crisis periods.

In terms of the liquidity ratio, cash rate is observed to increase post acquisitions for most groups and time periods during-credit crisis stage (Figure 2.7). This effect is different from the result from pre-credit crisis stage, and it shows the acquiring banks hold more liquid asset post acquisitions. This can be due from that during the financial credit crisis periods the acquiring banks post acquisitions act more conservative to hold more liquid asset for the purpose of stress period strategy or meeting withdrawal needs, or hold more cash aside to wait for potential more profitable investment opportunities post credit crisis.

Figure 2.7: Cash Rate Results - During-Credit Crisis



2.5.1.3 *Post-Credit Crisis Results*

The post-credit crisis stage restricts the data to the time periods between 2011 and 2014. There are three acquiring bank groups, namely Group 2012, Group 2013 and Group 2014. Table 2.6 presents the estimation results on the post acquisition impacts from each of the financial ratios which represent the performance measures. All the financial ratios presented in Table 2.6 are in terms of percentage unit except profit per employee which is in terms of dollar value.

For the capital adequacy ratio, during the post-credit crisis stage the acquiring banks show drops in the equity ratio for all post acquisition periods of Group 2012 and Group 2013 (Figure 2.8). The result is different from the pre-credit crisis stage and during-credit crisis stage as in these two stages the equity ratios show increase post acquisitions for the acquiring banks. It provides evidence that the equity ratio post acquisition change is sensitive to the stages in an economic cycle.

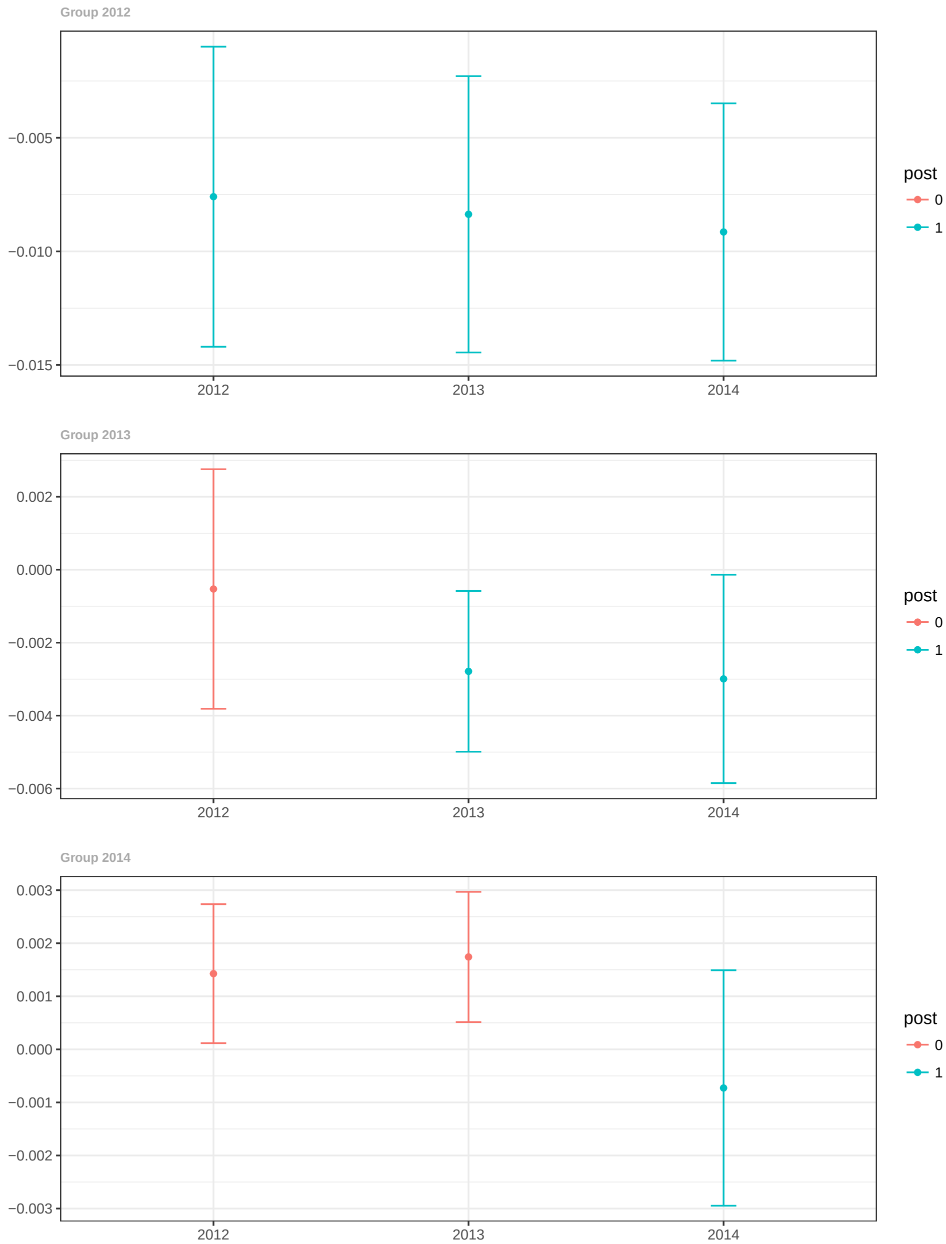
For the asset component ratios, the acquiring banks don't show statistically significant change on other real estate asset ratio and real estate loan asset ratio in all the post acquisition time periods for almost all groups. Total loan ratio shows increase for most acquiring bank groups and post acquisition time periods. The commercial and industrial loan ratios show statistically significant increase for all groups and post acquisition time periods in the post-credit crisis period, which is also observed for pre-credit crisis stage and during-credit crisis stage. In terms of bad asset ratios, for delinquent ratio significant positive effect from acquisition event is estimated for the Group 2012 and Group 2013 in all post acquisition time periods, while for non-performing loan ratio significant positive effect from acquisition event is estimated for the Group 2012 in time periods of 2013 and 2014. It provides more evidence on that the acquisitions increase bad asset ratios.

For the two management quality ratios investigated, no statistically significant effects are estimated for acquiring banks of all the acquiring groups in the post

Table 2.6: Financial Ratios Results - Post-Credit Crisis

FinancialRatio	Group2012			Group2013		Group2014
	2012	2013	2014	2013	2014	2014
EquityRatio	-0.76	-0.84	-0.91	-0.28	-0.30	-0.07
	(0.34)	(0.31)	(0.29)	(0.11)	(0.15)	(0.11)
TotalLoan	1.31	2.38	3.24	0.23	1.19	-0.79
	(0.40)	(0.63)	(0.71)	(0.38)	(0.56)	(0.32)
ReLoan	-0.26	-1.00	-2.24	0.01	-0.12	-0.80
	(0.34)	(0.76)	(1.05)	(0.63)	(0.85)	(0.51)
CniLoan	1.10	1.56	1.71	1.06	1.67	1.40
	(0.31)	(0.51)	(0.55)	(0.39)	(0.53)	(0.38)
OtherRe	0.01	0.06	0.08	0.01	0.04	-0.03
	(0.04)	(0.05)	(0.05)	(0.03)	(0.04)	(0.03)
Delinquent	0.10	0.14	0.15	0.07	0.11	-0.02
	(0.03)	(0.04)	(0.04)	(0.02)	(0.03)	(0.02)
NonPerforming	0.09	0.19	0.25	-0.01	0.04	-0.02
	(0.06)	(0.08)	(0.09)	(0.07)	(0.09)	(0.05)
NonOperatingExp	-0.17	0.17	0.06	0.02	0.06	-0.01
	(0.10)	(0.13)	(0.16)	(0.10)	(0.17)	(0.08)
ProfitPerEmployee	9	-7	7	-27	8	24
	(11)	(21)	(12)	(22)	(11)	(22)
ROE	-0.81	-2.19	-4.32	-2.96	-2.85	-2.79
	(1.36)	(1.53)	(1.44)	(1.29)	(1.85)	(1.33)
OperatingProfit	-3.04	2.70	4.65	2.47	8.64	1.07
	(3.75)	(4.28)	(5.13)	(2.79)	(4.48)	(2.07)
CashRate	0.03	0.37	0.25	0.28	0.30	0.19
	(0.20)	(0.32)	(0.34)	(0.14)	(0.20)	(0.15)

Figure 2.8: Equity Ratio Results - Post-Credit Crisis



acquisition periods. It provides evidence that no significant management quality change post acquisitions based on the two ratios investigated in the post-credit crisis periods.

For the two earning ratios chosen, return on equity is negative impacted from acquisition events for the groups and post acquisition time periods which show statistic significance, while no statistically significant impact is observed for operating profit ratio. The result is consistent with the ones from both pre-credit crisis stage and during-credit crisis stage.

For the liquidity ratio, most acquiring groups don't present statistically significant change for the post acquisition time periods except for Group 2013 in time period 2013 which shows increase on cash ratio.

2.5.2 Quantile Difference-In-Difference Analysis Estimation Results

This paper also investigates the quantile difference-in-difference effects from mergers and acquisitions on the acquiring banks for the financial ratios which represent performance measures. Like the group time difference-in-difference effect, it focuses on the mergers and acquisitions which increase the acquiring banks' assets by largest percentage during the observation time periods. It also investigates the data from three stages, namely pre-credit crisis stage, during-credit crisis stage and post-credit crisis stage. In the pre-credit crisis stage, it focuses on the acquisitions which happened in 2005. Likewise, it focuses on the acquisitions in 2009 for during-credit crisis stage and acquisitions in 2013 for post-credit crisis stage. The financial ratios which are analyzed in this section are equity ratio, delinquent asset ratio, non-performing asset ratio and return on equity. As been observed in the group time difference-in-difference estimation results, these ratios show significant changes for acquiring banks post acquisitions. This section adds the understanding that whether the change on each ratio variates when it is in the higher end or lower end of the original ratio's distribution. This paper selects the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile to draw analysis conclusions. Table 2.7 presents the result for all the three macroeconomic stages, and the impacts on the ratios are in terms of percentage.

Table 2.7: Quantile Difference-in-Difference Analysis Result

FinancialRatio	10 Quan.	25 Quan.	Median	75 Quan.	90 Quan.
PreCreditCrisis					
EquityRatio	0.54	0.81	0.72	0.70	−2.39
Delinquent	0.06	−0.01	0.08	−0.03	−0.09
NonPerforming	0.05	−0.02	−0.05	0.04	−0.32
ROE	−10.50	−2.76	−7.26	−2.23	−69.6
DuringCreditCrisis					
EquityRatio	−0.94	−0.09	0.02	0.28	1.33
Delinquent	0.19	0.02	0.19	0.19	−0.49
NonPerforming	0.42	0.85	1.38	1.53	3.64
ROE	−2.03	4.91	6.25	−6.77	−3.69
PostCreditCrisis					
EquityRatio	−3.22	−3.77	−1.89	−1.88	−7.44
Delinquent	−0.04	−0.17	−0.34	−0.63	−2.02
NonPerforming	−0.08	−0.09	−0.43	−0.78	−6.46
ROE	−0.30	−0.27	−0.56	−0.40	−1462

The result shows that the impacts from mergers and acquisitions on each financial ratio vary dependent on whether the financial ratio is at the higher end or lower end of its distribution. In the pre-credit crisis stage, for equity ratio, it shows some heterogeneity on the effect. From the low to median high end of the equity ratio distribution, the effects of mergers and acquisitions on the equity ratio are positive. For example, at 25th percentile, the equity ratio is estimated to increase by 81 basis points for acquiring banks after acquisitions. However for the high end of the equity ratio distribution, the effect of mergers and acquisitions on the equity ratio is negative. To be specific, at 90th percentile, the equity ratio is estimated to decrease by 2.39 percentage points for acquiring banks post acquisitions. For both delinquent assets ratio and non-performing assets ratio, the effects of the mergers and acquisitions for the acquiring banks also show heterogeneity dependent on the distributions. For return on equity ratio, the effects of the mergers and acquisitions on the acquiring banks are all negative across the distribution of return on equity but with some variation of effects magnitude. For instance, the return on equity is estimated to decrease by 2.76 percentage points for acquiring banks post acquisitions at 25th percentile, but the decrease magnitude is as high as around 70 percentage points at 90th percentile.

In the during-credit crisis stage, for equity ratio, it also shows some heterogeneity on the effects of mergers and acquisitions. At the low end of the equity ratio distribution, the mergers' effects on the equity ratio are negative. For example, the equity ratio is estimated to decrease by 94 basis points for acquiring banks post acquisitions at 10th percentile. In contrast, from the median to the high end of the equity ratio distribution, the mergers effects on the equity ratio are positive. For delinquent asset ratio, it sees positive effects of mergers and acquisitions for the acquiring banks from low end (10th percentile) to median high end (75th percentile) of its distribution, while at the high end (90th percentile) of its distribution, it sees negative effects from acquisitions. For non-performing assets ratio, it sees positive effects of mergers and acquisitions for the acquiring banks across its distribution and the positive magnitude increases from low end to high end of its distribution. For return on equity ratio, it sees negative mergers effects at the low end and the high end of its distribution for the acquiring banks, while it sees positive mergers effect at the median of its distribution for acquiring banks.

In the post-credit crisis stage, all the four ratios investigated display negative mergers and acquisitions effects for the acquiring banks across their distributions respectively. However, the magnitudes of the effects show some extent of heterogeneity. For example, the equity ratio is estimated to decrease by 3.22 percentage points for acquiring banks post acquisitions at 10th percentile, while the equity ratio is estimated to decrease by 7.44 percentage points for acquiring banks post acquisitions at 90th percentile.

2.6 Conclusion

The mergers and acquisitions in the US banking industry have impacts on the acquiring banks' performance in terms of financial ratios implied by CAMEL measure. This paper uses both group time difference-in-difference method and quantile difference-in-difference method to analyze the impact of mergers and acquisitions on the acquiring banks. The impacts are analyzed for three stages in an economic cycle, namely, the pre-credit crisis stage, the during-credit crisis stage and the post-credit crisis stage.

Among the performance measures investigated, not all the ratios are statistically significantly impacted by mergers and acquisitions. Five ratios show statistically significant impact from mergers and acquisitions for all the three time periods using group time difference-in-difference method. To be specific, equity ratio increases after mergers and acquisitions for acquiring banks in the pre-credit crisis stage and during-credit crisis stage while it decreases after acquisitions in the post-credit crisis stage. For all the three stages in an economic cycle, it sees an increase on the commercial and industrial loan ratio for the acquiring banks after mergers and acquisitions, which implies that the mergers and acquisitions affect the acquiring banks to make more commercial and industrial loans among all the loans and to restructure the acquiring banks' loan weight more on the traditional commercial and industrial loans. For both delinquent asset ratio and non-performing asset ratio, they are estimated to increase for acquiring banks post mergers and acquisitions in all the three stages in an economic cycle, which implies the acquiring banks have more bad assets ratio post mergers and the adverse impact doesn't go away along the time post mergers. It may result from the acquisitions of target banks with higher bad assets ratios and thus the acquisitions increase the acquiring banks' overall risk post mergers. For the earning ability in terms of return on equity, it sees decrease on this ratio for all the three time periods for the acquiring banks, which implies that post acquisitions the acquiring banks have less profit in terms of return on equity and hence it doesn't provide the evidence to support that the banks should make mergers and acquisitions for the purpose of realizing gaining profit for the shareholders. Among other ratios which don't show statistically significant impact from mergers and acquisitions for all the three stages, the increase in cash ratio post acquisitions for most groups in the during-credit crisis stage can be due from that the acquiring banks act more conservative to hold more cash as part of stress period strategy or waiting for potential more profitable investment opportunities post credit crisis. In addition, most of time there are no statistically significant changes post mergers for the two ratio in the category of management, which can be explained by that the management is more affected by the acquiring banks and it is not significantly changed after mergers.

The quantile difference-in-difference analysis shows that in most cases the direction of acquisition impact is consistent with the results from group time difference-in-difference results for the performance measures, for instance the return on equity ratio is estimated to decrease post mergers and acquisitions across the distribution of itself in the pre and post-credit crisis stages. However it also shows variations of the mergers and acquisitions impact on each financial ratio depending on where the ratio is at its distribution prior to the mergers, and sometimes this variation is significant enough to make the post acquisition impacts to be of two directions. For example, in the pre-credit crisis stage, the equity ratio is estimated to increase by 81 basis points at 25th percentile for acquiring banks post acquisitions, while the equity ratio is estimated to decrease by 2.39 percentage points at 90th percentile for the acquiring banks post acquisitions.

Overall, using the two difference-in-difference methodologies enables this paper to provide extensive empirical evidence for the mergers and acquisitions effects. The group time difference-in-difference analysis provides a view to see how the different acquisition timings affect the performance measures over post acquisition time periods. The quantile difference-in-difference analysis provides empirical view to see how acquisition effects variate across the performance measures' distributions. With the combination of the results from the two methodologies, it can provide the empirical evidence for the banks which consider to take acquisitions to make decisions.

CHAPTER 3

PREDICTION OF U.S. BANK STATUS USING MACHINE LEARNING VS. MULTINOMIAL LOGISTIC REGRESSION

3.1 Introduction

Traditional economic research mostly focus on understanding a matter of interest and explaining it using factors with reasonable mechanism. For example, the first chapter of my essays analyzes the financial ratios and how they affect the risks of bank takeover or bank failure. While this strand of research is mainstream and mostly uses traditional econometric methods to explain the underlying relationship, there is an expanding strand of research which focus on what factors collectively predict the matter of interest and the goal is to increase the prediction accuracy. With the accurate prediction, decision makers can make judgments with expectation of realizing optimal predicted outcome. Among the available techniques, machine learning is one prediction technique worth exploring.

The goal of this paper is to compare both traditional parametric statistical regression methodology and machine learning methodology in the prediction field. It compares two methods, namely multinomial logistic regression which is a representative of the parametric statistical regression method, and eXtreme Gradient Boosting (XGBoost) which is a representative of non-parametric machine learning method. The prediction is on the risks of bank takeover [1] and bank failure facing by U.S. banks. It uses the U.S. banking mergers and acquisitions data from 2002 to 2014. The inputs consist of selected financial ratios which represent five aspects of CAMEL measures, as well as some bank level information such as age and Herfindahl-Hirschman Index (HHI) in the local market. The comparisons include prediction accuracy, and the most important features for the predicting problem between the two methods. It also applies the model agnostic interpretation SHapley Additive exPlanations (SHAP) value to interpret the result from machine learning method and thus compare the inputs contribution on the targets from the two methods. The comparison is conducted in two ways. The first method includes developing the model and evaluating the model performance based on whole length of data from 2002 to 2014. This method allows me to fully utilize the collected data with no missing information. The second method includes developing the model using partial data (in-sample data) and evaluating the model performance using the left out data (out-of-sample data). This method mimics how the model is used in the real prediction cases.

The contribution of this paper is three fold. First, this paper extends the banking mergers and acquisitions literature to the prediction research strand. The potential investors can use the result to predict the bank failure or bank takeover to make investment decisions. Second, it compares the traditional logistic regression method with machine learning methodology of XGBoost on the prediction of bank takeover and bank failure, hence it provides empirical evidence to enrich the research literature on understanding how well different methodologies work on the prediction of the bank risks of failure and takeover. Last, it gives an empirical example to understand the machine learning technique of XGBoost in the way that how each feature contributes

[1]This risk type refers to the takeover by an independent bank which doesn't share the same ultimate parent bank as the target.

to the predicted bank failure and bank takeover.

When applying machine learning to predicting, the process of guessing the functional forms typically is not required while not compromising the prediction performance. When a functional form cannot be guessed at, the machine learning crunches sorts through the possibilities. Hence one potential advantage of machine learning is that it is valuable when the functional form of the outcome likelihood is not initially known and cannot even be guessed. In the meanwhile, the reluctance to use machine learning ensues as the interpretation of the final machine learning model may be difficult. When achieving reasonable prediction performance is not the only goal, the interpretation of the machine learning models becomes essential for wide usage of machine learning techniques over standard econometrics. For instance, in the traditional linear regression, the estimates of coefficients give intuitive interpretation of how the independent variables affect the dependent variables. In contrast, although the gradient boosting or random forest techniques use the features to predict the results, the relationship between features and target variable can not be simply directly obtained. In addition, the counter-intuitive variables can be relatively easier to identify under standard econometrics than machine learning model which is heavily data driven. To address the concern, many model feature interpretation techniques are under development and there is much progress has been seen in this strand of research.

This paper uses the same features for both machine learning method of XGBoost and multinomial logistic regression model. The features used are intuitive and explained in the first chapter. Towards the concern of interpretation of the machine learning model result, SHAP analysis is utilized in this paper to unveil how the machine learning model prediction is achieved by the features, and in what way the machine learning model works differently from traditional parametric statistic model.

The comparisons of the two methodologies are based on practical questions of predicting bank risks. I consider two risks, bank takeover and bank failure. I assume there is a three point sequence for a bank failure, consisting of: (1) the bank has been in trouble; (2) the trouble cannot go away with continued operation; (3) no takeover is achieved before it eventually fails or government steps in. The bank failure would directly affect all the stakeholders from shareholders to employees, sometimes it also can cause the catastrophic results for the whole economy. For instance, the collapse of Lehman Brothers directly affected the whole US financial industry and the extent of the impact went even further. Hence the bank failure prediction can help banks to be alert of this risk and thus make actions accordingly to avoid it. Similar to the bank failure, the bank takeover can also imply bank trouble. The target bank of a bank takeover would possibly undergo the same first two steps as in the bank failure sequence, but there is a takeover achieved without government assistance in the end. Besides implying bank trouble, the bank takeover can also be a symptom of being healthy and small. The bank takeover would impact both the target banks and the acquiring banks. The target bank of a bank takeover would be integrated into the acquiring bank and subject to the acquiring bank's strategy, and sometimes the shareholders of the original target bank can receive good rewards for the takeover. The acquiring bank of the takeover would consolidate and undergo some changes through the time post takeover, which was analyzed in second chapter. Overall, to predict the risk of bank takeover can help banks make decisions/actions to either go for or avoid this event.

In sum, this paper provides evidence that XGBoost method gives better prediction accuracy if using the whole length of US banking mergers and acquisitions data from 2002 to 2014 (first practice), but the outperformance of XGBoost method is not obvious if developing the model in restricted in-sample data and evaluating the performance using the out-of-sample data (second practice). It also shows that the most important features from XGBoost method and multinomial logistic regression method are highly aligned. The SHAP analysis on XGBoost model shows that the features contribute to the targeted risks in a non-linear way. Standard econometrics can do similar work of considering non-linearity, but additional work of checking the shape may be put in front to incorporate more complex form. Between bank failure and bank takeover, both two methodologies can give better prediction accuracy on the risk of bank failure than the risk of bank takeover.

3.2 Literature Review

For the strand of research which predict the bank risks, financial ratios are mostly used as predictors. The reason is that the financial ratios are the operating results during some time periods for firms. In addition, financial ratios can imply the current health of the firms, thus they contain information for risks facing by firms. The financial ratios which are commonly used reflect some components from CAMEL measure (capital adequacy, asset quality, management, earning ability and liquidity). For instance, Alam et al (2000) [1] use financial ratios such as return on asset (earning ability), and non-performing loans to total assets ratio (asset quality) to identify the bank bankruptcy. Canbas et al (2005) [11] use financial ratios such as quick ratio (liquidity), income ratio (earning), equity ratio (capital adequacy) to detect of banks which are experiencing serious problems. Another example is Wheelock and Wilson (2000) [41], who use different financial ratios, such as capital ratio (capital adequacy) and cost-efficiencies (management) to estimate the risk of bank failure and bank takeover.

Kumar and Ravi (2007) [28] present a comprehensive review of the research which has been done to predict the bankruptcy by banks and firms between 1968 and 2005. It gives a view of the different research categorized by the different methodologies, including machine learning methodologies such as decision trees, neural networks.

With the goal to predict the bankruptcy events, the prior research have explored many techniques. The analysis of bankruptcy can trace back as early as 1968. Altman (1968) [2] employed a multiple discriminant statistical methodology to predict bankruptcy to the manufacturing corporations with financial ratios as inputs. Martin (1977) [31] and Ohlson (1980) [33] analyzed the bank bankruptcy using logistic regression approach. From late 1980s, artificial intelligence methods including machine learning methods become successfully applied to the bankruptcy prediction. More research have utilized both traditional statistic methods and machine learning methods to contribute to the understandings of the methods as well as to improve the prediction performance. Many show that the designed artificial intelligence methods have better prediction performance than the statistic models. For instance, du Jardin (2010) [17] evaluated the prediction accuracy of different models using different classification methods to see their ability to predict financial failures, and found that a neural network based model lead to better results than other methods. Another research from Iturriaga et al (2015) [24] showed a similar conclusion that a neural network method performed better prediction ability in bank failures. It showed that a combined multi-layer perceptrons and self-organizing maps outperforms other traditional models in detecting US bank failures. However, the comparisons between the traditional statistic methods and machine learning models don't lead to the unanimous conclusion of which method is always better. The machine learning models which are more complex, can capture the non-linear relationship between the predictors and the target variables. In the meanwhile, machine learning techiniques are data hungry and the performance is prone to the data. van der Ploeg et al (2014) [35] found using modern modelling techniques such as machine learning modelling may need over 10 times per variable to realize small outperformance than traditional statistic parametric modelling.

Towards the machine learning model interpretation, the research on how to interpret a machine learning is drawing more and more attention recently. Machine learning models are normally interpreted with model agnostic interpretability, as machine learning models are complex and cannot be self-explained. Ribeiro et al (2016) [36] analyzed the model agnostic on the machine learning and concluded that model agnostic interpretability was a key component for machine learning models becoming more applicable and trustworthy. Through the development of model agnostic interpretability, surrogate models were among the early developed interpreation methods and they were seeking to interpret the output through approximated interpretable models. Unceta et al (2018) [38] proposed a method to obtain global explanations method to understand trained black box classifiers using private residential mortgage default data. Recently, the concept of the Shapley value from cooperative game theory is applied to the machine learning interpretability. SHapley Addictive exPlanations (SHAP) by Lundberg et al (2017) [30] is based on the Shapley value. SHAP analysis can not only explain individual predictions, but also provide global interpretations. Datta et al (2016) [14] proposed a quantitative input influence method which is generalized version of Shapley ratio to interpret machine learning models and Bracke et al (2019) [8] applied this method to predict mortgage defaults.

3.3 Methodology

This paper differentiates the bank risks of failure and takeover. As there are more than one risk, hence it selects multinomial logistic regression as a representative of traditional parametric method. For machine learning method representative, this paper uses XGBoost machine learning method from Chen and Guestrin (2016) [12].

3.3.1 Multinomial Logistic Regression

Multinomial logistic regression is a widely used method in the case when the target variable is categorical and has more than 2 outcomes. In this paper, there are three outcomes for each bank during a time period, namely the bank failure, the bank takeover, and the bank continuation as is. To put it into a standard multinomial logistic regression setup, let $Y_{it} = 0$ stand for the baseline risk, namely the bank i neither is acquired nor fails in period t. Let $Y_{it} = 1$ stand for that the bank i fails in period t. Let $Y_{it} = 2$ stand for the case that the bank i is acquired in period t. This represents the risk event of bank takeover by an independent bank. Let X_{it} stand for a vector of the input features for bank i in period t. β_j is a vector representing the corresponding parameter estimates of the input features for risk event j, where $j = 1$ refers to the risk of bank failure and $j = 2$ refers to the risk of bank takeover. This paper uses financial ratios implied in CAMEL measures and some other bank level characteristic features. The probabilities of non-baseline category responses are modeled as:

$$P(Y_{it} = j|X_{it}) = \frac{e^{X_{it}\beta_j}}{1 + \sum_{h=1}^{2} e^{X_{it}\beta_h}}, j = 1, 2 \tag{3.3.1}$$

And the probability of baseline category response is:

$$P(Y_{it} = 0|X_{it}) = \frac{1}{1 + \sum_{h=1}^{2} e^{X_{it}\beta_h}} \tag{3.3.2}$$

After simple manipulation, it can be shown that the log form of the odds ratio for each non-baseline category response relative to the baseline category response exhibits a linear relationship with the input features. For illustration, one unit increase of the input feature x for bank i at time t will change the log form of the odds ratio between bank failure risk event relative to baseline state by β_{1x} unit during t period, where the β_{1x} is the coefficient specific to the input feature x.

3.3.2 Machine Learning Method

Among the machine learning methodologies, boosting is a widely used and highly effective method. Fundamentally, boosting doesn't achieve to find the solutions to prediction problems. Instead, it is a glorifying non-parametric function estimator and seeks for a shortcut. Conceptually, boosting consists of using several weak prediction models to produce a stronger one. For regression and classification problems, the gradient boosting technique can be used. The general idea of boosting is to fit a sequence of target variables which are on top of one base learner, and this sequence of target variables come from a series of the errors resulted from fitting the learners from the prior step. To understand it in a math setup, the goal is to guide a model F to predict the target value by minimizing a target function, which is normally an algorithm representing a loss function. When attempting to find the optimal model F, the gradient boosting has several stages M, while at each stage m, when $1 \leq m < M$, the model F_m is assumed to be imperfect. Hence in the next stage $m+1$, the model can be improved by gradient boosting algorithm of adding an estimator h. Thus the model at stage $m+1$ is as below:

$$F_{m+1}(x) = F_m(x) + h(x) \tag{3.3.3}$$

As the goal is to find a perfect h to get the value of observation y, hence the goal is transformed to fit h to the residual $y - F_m(x)$. The algorithm to find h is key to the method with normally a form of the loss functions, and sometimes also an additional regularization term.

This paper uses the XGBoost method by Chen and Guestrin (2016) [12] to predict the bank takeover or failure. XGBoost is described as a scalable end-to-end tree boosting system. The XGBoost has received wide attention in machine learning contests. The method was originated from Friedman et al (2000) [18]. Chen and

Guestrin (2016) [12] made minor improvements in the regularized objectives, the improvements have brought benefits to be used in practice. To understand how the XGBoost method works, this paper summarizes it in the following set up. The goal of the XGBoost method is to find a set of weak predictions f_m to produce a final prediction $\hat{y}_i$ based on the features x_i.

$$\hat{y}_i = \varphi(x_i) = \sum_{m=1}^{M} f_m(x_i) \tag{3.3.4}$$

For each bank i in our case, the goal is to learn a set of prediction f_m to get the event prediction $\hat{y}_i$. To learn a set of functions, XGBoost minimizes a regularized objective which consists of two parts: a differentiable convex loss function l which measures difference between actual target y_i and predicted target $\hat{y}_i$, and a penalization function Ω on the complexity of the model. In this paper, the loss function part of XGBoost is the same loss function used in multinomial logistic regression. The regularized objective function is:

$$L(\varphi) = \sum_{i} l(\hat{y}_i, y_i) + \sum_{m} \Omega(f_m) \tag{3.3.5}$$

$$where\ \Omega(f) = \gamma T + \frac{1}{2}\lambda \|\mathbf{w}\|^2 \tag{3.3.6}$$

In penalty function Ω, γ and λ are constants, where γ is the minimum loss reduction required to make a further partition on a leaf node of the tree, and λ is L2 regularization term on weights. Both γ and λ can be adjusted through hyperparameter adjustment in the XGBoost method. T is the number of the leaves in the tree, and leaf weights $\mathbf{w}$ correspond to each f_m.

As the above tree ensemble model cannot be optimized through traditional optimization methods, hence Chen and Guestrin (2016) [12] added greedy algorithm learner f_m to each iteration to the objective. The objective at iteration m becomes::

$$L^{(m)} = \sum_i l(y_i, \hat{y_i}^{m-1} + f_m(x_i)) + \Omega(f_m) \tag{3.3.7}$$

After taking the second-order approximation of $L^{(m)}$, the optimal weight w_j^* of leaf j as well as corresponding optimal value $\hat{L}$ can be estimated in terms of first order gradient statistic on the loss function (g_i) and second order gradient statistic on the loss function (h_i). Here g_i and h_i are evaluated at:

$$g_i = \partial_{\hat{y_i}^{m-1}} l(y_i, \hat{y_i}^{m-1}) \tag{3.3.8}$$

$$h_i = \partial^2_{\hat{y_i}^{m-1}} l(y_i, \hat{y_i}^{m-1}) \tag{3.3.9}$$

For a fixed tree structure $q(x)$, define $I_j = \{i|q(x) = j\}$ as the leaf j instance set. The specific form of w_j^* of leaf j and corresponding optimal value $\hat{L}$ are estimated as below:

$$w_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \tag{3.3.10}$$

$$\hat{L}^{(m)} = -\frac{1}{2} \sum_{j=1}^{T} \frac{(\sum_{i \in I_j} g_i)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma T \tag{3.3.11}$$

3.3.3 Machine Learning Model Interpretation

Choosing a machine learning model over other traditional statistic model based only on performance accuracy is not adequate. The ability to interpret a machine learning model is also essential. Machine learning models are known to be complex and don't have specific model specifications like traditional statistic methods. Some attention has turned to intepreting the coefficients or layers estimated in machine learning, and the enhancement of machine learning model interpretation has been made substantial progress in the recent machine learning research. In this strand of the research, the goal is not necessarily trying to explain the model itself, but to find the important features of the model. Based on the salient features of the model, the examination of feature intuitiveness can be conducted to select a better model. This paper uses two ways to interpret machine learning models.

First, it uses the feature importance measure technique to examine the intuitiveness of top features. For the XGBoost method, the feature importance can be estimated based on the feature rankings by their contribution to the loss reduction when the features are used for splitting. This interpretation doesn't directly capture the feature interactions.

Second, it uses SHAP analysis to estimate the relationship between the features and the contributions to the targets of risks. This approach started with the Shapley-based approach, which was an instance based approach, and then proceeded to give global explanations. The Shapley value is a concept originating from cooperative game theory by Shapley in 1953 [37]. The basic concept in its application in the machine learning model interpretability is that all the features work together to achieve certain performance accuracy. The contribution from one feature is not just from itself to the final performance, but also from how it affects other features in the prediction. SHAP value has considered all the combinations and the orders of features and decided the marginal impact from with and without the feature. Hence the big advantage of using SHAP analysis is that it considers the feature interaction in a comprehensive way. As an example of how to utilize Shapley ratio, Bracke et al (2019) [8] proposed a quantitative input influence measure to interpret the machine learning model with extension of the Shapley ratio.

3.4 Data and Predicted Results

3.4.1 Data

The data used in this paper is the U.S. banking mergers and acquisitions data which was obtained from National Information Center (NIC). This data is maintained by Federal Reserve and it contains basic information about both acquiring bank and the target bank which are engaging an acquisition. This paper focuses on the side of banks which are acquired or failed, hence the data was filtered accordingly to fit the goal. For the banks which are taken over, this paper only considers the banks which are acquired by independent banks and stop existing as they transfer at least 90% to the acquiring banks as the acquired banks. The time periods were narrowed down to between 2002 and 2014 for the consideration of balancing between the difficulty of achieving data and drawing meaningful implication.

The features which are used to predict the bank failures or takeovers were obtained from FDIC reports. To be specific, FDIC call reports provide data to derive the bank level financial data and FDIC all reports provide some other information to the bank level such as bank's age and operating location.

The banking merger and acquisition data, as well as financial ratios are analyzed at the annual frequency. Compared to the quarterly frequency, the data in the annual frequency can provide more risk events in each period and thus can suit better to the goal of the prediction. To compare the prediction from both multinomial logistic regression and XGBoost method, the features used are the same for both methods. Using the same features for analysis can eliminates the model performance difference potentially caused by using different features. The feature values which are one year ahead of the acquisition or bank failure events are considered, as generally these events take time and one year prior to the events is a more relevant time period. Table 3.1 summarizes the definitions of the targeted variable and the features.

Table 3.1: Target and Feature Definition

Name	Definition
Target Variable	
BankStatus	0 means the bank continues to operate as is; 1 means the bank fails; and 2 means the bank is taken over by an independent bank
Features	
EquityRatio	total equity / total assets
TotalLoan	total loans/total assets
ReLoan	real estate loans/total loans
CniLoan	commercial and industrial loans/total loans
OtherRe	other real estate owned / total assets
Delinquent	past due 30 days through 89 days and still accruing/total assets
NonPerforming	nonperforming loans/total assets
NonOperatingExp	noninterest expense / total assets
PAT	net after tax income / total assets
OperatingProfit	(net interest income - operating expenses)/total interest income
CashRate	(federal funds purchased and securities purchased under agreements to resell - fed funds sold and securities sold under agreements to repurchase)/total assets
Age	log transform of the bank age
AssetSize	log transform of the bank asset size
AssetGrowth	year over year asset growth rate
HHI	calculated county level HHI index
ForeignDepositFlag	indicator whether the bank has foreign deposits

The data structure is in panel form and spans from 2002 to 2014. Some of the acquired banks or failed banks don't have the FDIC information, hence these acquisitions are excluded from the analysis. This exclusion is to focus the prediction on the banks which file FDIC reports and these banks are representatives of the U.S. banks. Between 2002 and 2014, there are 1474 bank takeovers and 420 bank failures among 93455 data entries. Table 3.2 shows the summary statistics for the bank status of failure and bank takeover respectively, and the features.

Table 3.2: Summary Statistics for Targets and Features

Statistic	Mean	St. Dev.	Min	Max
Targets				
Failed	0.004	0.067	0	1
Acquired	0.016	0.125	0	1
Features				
EquityRatio	0.109	0.043	0	0.959
TotalLoan	0.635	0.156	0	1
ReLoan	0.684	0.196	0	1
CniLoan	0.035	0.084	0	1
OtherRe	0.004	0.010	0	0.290
Delinquent	0.008	0.008	0	0.159
NonPerforming	0.011	0.015	0	0.321
NonOperatingExp	0.072	0.076	−0.172	7.980
PAT	0.005	0.008	−0.577	0.286
OperatingProfit	0.016	4.79	−1,040	5.6
CashRate	0.017	0.061	−0.854	0.920
Age	3.850	1.141	0	5.403
AssetSize	11.927	1.318	7.815	21.409
AssetGrowth	0.137	6.021	−0.844	1,558
HHI	3,480	2,496	338	10,000
ForeignDepositFlag	0.021	0.143	0	1

3.4.2 Results - Whole Data

In this section, it presents the prediction results from both traditional multinomial logistic regression method and XGBoost machine learning method to see the prediction accuracy. It leverages the whole data which spans from 2002 and 2014 to build models, so that it gives a broad ex post view of how well the models work. As both methods are based on the same features, hence the comparison is direct and can reflect the prediction ability from the methods themselves. In addition, from both methods, the most important features determining the prediction outcomes are compared to see the similarity and difference from both methods. Furthermore, SHAP values for XGBoost method are also evaluated to see how each feature affects the targeted risks.

3.4.2.1 Multinomial Logistic Regression Results - Whole Data

As there are two risks, namely bank failure and bank takeover, a multinomial method is used. Table 3.3 shows multinomial regression coefficient estimates.

Table 3.3: Parameter Estimates - Multinomial Logistic Method - Whole Data

	Dependent variable:	
	Failure	Takeover
EquityRatio	-36.978^{***}	-7.198^{***}
	(0.00004)	(0.0001)
TotalLoan	5.073^{***}	0.190^{***}
	(0.0004)	(0.001)
ReLoan	1.205^{***}	0.704^{***}
	(0.0005)	(0.001)
CniLoan	1.598^{***}	1.180^{***}
	(0.00004)	(0.0003)
OtherRe	8.469^{***}	-5.712^{***}
	(0.00001)	(0.00002)
Delinquent	36.713^{***}	-5.835^{***}
	(0.00001)	(0.00001)
NonPerforming	20.170^{***}	4.496^{***}
	(0.00003)	(0.00004)
NonOperatingExp	-53.031^{***}	-45.185^{***}
	(0.00003)	(0.00002)
PAT	-59.181^{***}	-52.980^{***}
	(0.00000)	(0.00003)
OperatingProfit	-0.083^{***}	-0.047^{***}
	(0.005)	(0.003)
CashRate	1.684^{***}	2.189^{***}
	(0.00000)	(0.00001)
Age	-0.178^{***}	-0.325^{***}
	(0.002)	(0.021)

Table 3.3: (continued)

	Dependent variable:	
	Failure	Takeover
AssetSize	0.041***	−0.267***
	(0.007)	(0.007)
AssetGrowth	−0.106***	−1.820***
	(0.00004)	(0.001)
HHI	−0.00001	0.00003***
	(0.00002)	(0.00001)
ForeignDepositFlag	−0.857***	−0.195***
	(0.00002)	(0.0002)
Constant	−4.456***	3.143***
	(0.001)	(0.0003)

Note: *p<0.1; **p<0.05; ***p<0.01

The value in parenthesis is the feature's standard deviation

Table 3.3 results indicate that all features are significant except HHI in the multinomial logistic regression. The model specification is interpreted as how each feature affects log odds ratio of that risk event and in what direction relative to the baseline risk of bank continuing to operate as is. For example, if the equity ratio increases by one percent, the log odds ratio of bank failure relative to baseline state of continuing to operate as is would decrease by 37 percent, and the log odds ratio of bank takeover relative to baseline state of continuing to operate as is would decrease by 7 percent. Increasing any feature with positive risk parameter estimate would increase the occurrence chance of that risk event relative to the baseline risk. The opposite is true for the interpretation of features with negative parameter estimates.

After estimating the multinomial logistic regressions, the predicted outcome for each bank in the panel data is estimated. Firstly, as there are three states (bank continuity, bank failure and bank takeover) in total, for each bank at a point of time, the probability on each of the three states is predicted. The predicted state for a bank at that time point would be the state with largest probability of the three. After deriving the predicted state for the data, then the comparison between predicted state and actual state would be conducted. Table 3.4 shows the confusion matrix for the whole data from multinomial logistic regression, and Table 3.5 shows the selected statistics from the comparison.

Table 3.4: Confusion Matrix - Multinomial Logistic Method- Whole Data

		Actual Value			
		Base	Failure	Takeover	Total
Predicted Value	Base	91490	300	1458	93248
	Failure	63	118	9	190
	Takeover	8	2	7	17
	Total	91561	420	1474	93455

Table 3.5: Selected Statistics - Multinomial Logistic Method - Whole Data

	Base	Failure	Takeover
Sensitivity	0.99922	0.280952	0.0047490
Precision	0.98115	0.621053	0.4117647
Detection Rate	0.97897	0.001263	0.0000749
Kappa:			0.122

The confusion matrix of the multinomial logistic regression provides the model performance in terms of the accuracy in this categorical problem to predict the bank failure or takeover. The columns stand for the counts from the actual observed data, while the rows stand for the counts from the model prediction. The cells in the diagonal places represent the counts where the actual observed state coincides with predicted state. For instance, 118 banks which are observed to fail are also predicted to fail. The cells which are not in the diagonal places represent the cases when the predicted state contradicts the observed state. For instance, there are 63 banks which are observed to continue to operate as is, but they are predicted to fail. Although dominant volume of banks are in baseline status, the bank failure and bank takeover are the risk events which this paper analyzes. From the model prediction result it can be seen that the multinomial logistic regression predicts more baseline cases than the actual baseline cases (91561 cases are observed to be baseline state and the model predicts 93248 baseline state), while it predicts less failed cases and acquired cases than the actual cases.

The statistic sensitivity is true positive rate, which shows the proportion of actual observed events which were predicted to be events. There are 28% (118/420) actual failed banks were predicted to be failed, while only 0.5% (7/1474) actual acquired banks were predicted to be acquired. It implies that the multinomial logistic regression works better in predicting the bank failures than bank takeover in the measure of sensitivity. The statistic precision is the positive predictive value, which shows the ratio of the correct event predictions over all the predicted events. For instance, precision statistic of bank failure event is 62% which is derived by using predicted correct bank failed events counts (118) divided by all the predicted failed bank counts (190). The precision ratio of bank takeover is 41% (7/17), which means among all the predicted acquired bank events, 41% are observed real bank takeover cases. Hence from the perspective of the precision, the model performs better in the risk of bank failure than the risk of bank takeover as well. Detection rate is another statistic, which shows detected correct events percentage among all the observations. For example, among all the 93455 bank cases, 118 bank failures are correctly predicted, hence the detection rate for the bank failure is 0.13% (118/93455). Similarly the detection rate for the risk of bank takeover is 0.01% (7/93455). From the perspective of overall detection rate, the model can detect more true failed cases than the true acquired cases among all the population. One thing to note is that the statistics of detection rate cannot be used alone to determine the prediction accuracy, and it should be used combined with other ratios such actual risk event rate. For instance, although the detection rate for bank failure is only 0.13%, the actual bank failure rate is not relatively very high with value of 0.45% (420/93455).

One consolidated important statistic to evaluate the performance of the prediction is Kappa statistic. In the confusion matrix, the Kappa value measures the percentage of all the counts in the main diagonal and then adjusts for the amount of agreement due to chance only. The values from main diagonal are the counts on the banks when their predicted events agree with actual events for the three states. The performance cannot be evaluated only based on the values in the diagonal, as even random guess would make some degree of agreement. This paper calculated Kappa values to evaluate the model performance. The formula of Kappa's value is calculated based on p_{agree} and p_{random}. p_{agree} is calculated as:

$$p_{agree} = p_{BB} + p_{FF} + p_{TT} \tag{3.4.1}$$

p_{agree} is proportion of the total agreement between predicted and observed for the three states among all the population, and hence it is the sum of the proportions of the three risk banking states from diagonals. Here p_{BB} is ratio of the counts where both predicted state and actual state are baseline case over all the counts in the observed population (91490/93455). Similarly p_{FF} and p_{TT} stand for the agreements for failure state and takeover state.

$$p_{random} = p_{PredictB} * p_{ActualB} + p_{PredictF} * p_{ActualF} + p_{PredictT} * p_{ActualT} \tag{3.4.2}$$

p_{random} is the ratio of agreement coming from when the predicted cases and actual cases are completely independent. $p_{PredictB}$ is the ratio of predicted total baseline counts over total population (93248/93455), while $p_{ActualB}$ is the ratio of actual total baseline counts over total population (91561/93455). Similar definitions are set for failure case and takeover case.

After calculating p_{agree} and p_{random} , the Kappa value is calculated as:

$$Kappa = \frac{p_{agree} - p_{random}}{1 - p_{random}} \tag{3.4.3}$$

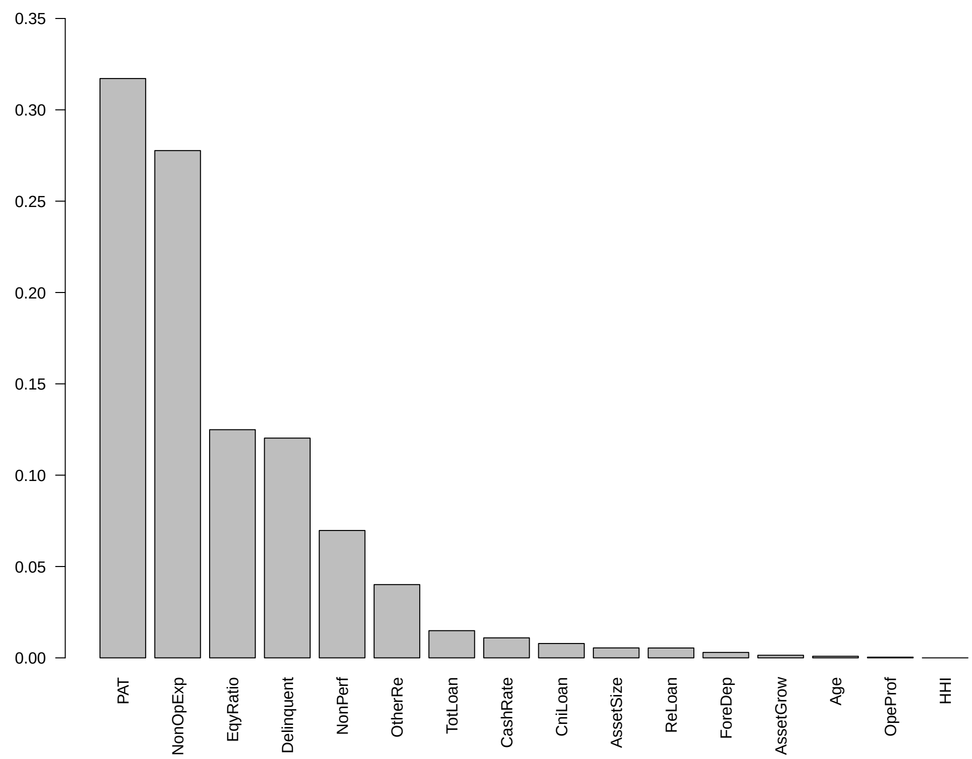
In general, the Kappa value ranges between -1 and 1. The closer the Kappa value is to 1, the more aligned are between the predicted and actual events. If the outcome is predicted by just random guess, the Kappa value would be zero. Hence a positive Kappa value implies the model performs better than random guess. In this regression, the Kappa value of 0.122 implies the performance is better than random guess.

Another examination of the multinomial logistic regression result focuses on the variable importance. In the regression parameter specification, it shows the relationship of how each feature affects the log transform of the odds ratio, but it doesn't show the variable importance to the target variable. This paper also checks the variable importance which represents the ability in mean decrease of impurity in each event category. Features with high feature importance values mean they play an important role in segregating the banks to different event categories. Figure 3.1 shows the variable importance from the multinomial logistic regression result. It can be seen that the top five important variables are net after tax income ratio, non-operating expense ratio, equity ratio, delinquent ratio and non-performing asset ratio, while the least important variable is HHI index.

3.4.2.2 Machine Learning Model - Whole Data

This paper also uses XGBoost method to predict the bank failure and bank takeover. It uses whole data and evaluates the performance from XGBoost. The machine learning model specification is not estimated as traditional statistic model, hence there is no exact equation to represent model parameter specification. The

Figure 3.1: Variable Importance - Multinomial Logistic Method - Whole Data



machine learning model is normally used for prediction, hence the prediction accuracy is evaluated. Table 3.6 shows the confusion matrix from XGBoost and Table 3.7 shows the major statistics on the confusion matrix.

Table 3.6: Confusion Matrix - XGBoost Method - Whole Data

		Actual Value			
		Base	Failure	Takeover	Total
Predicted Value	Base	91401	251	1305	92957
	Failure	45	158	19	222
	Takeover	115	11	150	276
	Total	91561	420	1474	93455

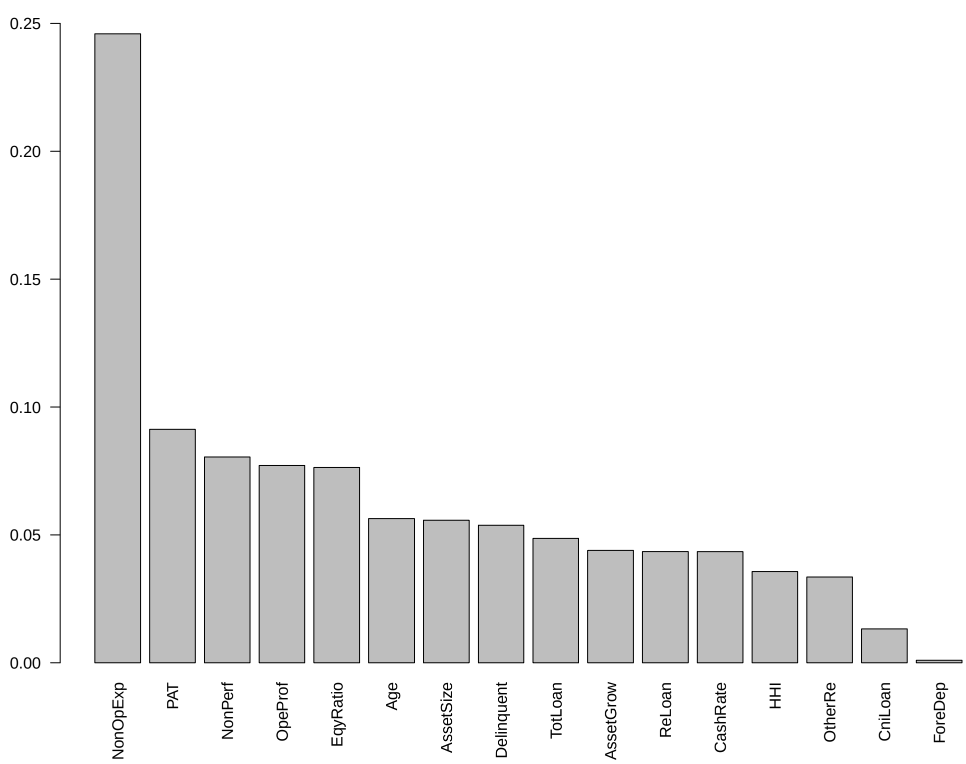
Table 3.7: Selected Statistics - XGBoost Method - Whole Data

	Base	Failure	Takeover
Sensitivity	0.9983	0.376190	0.101764
Precision	0.9833	0.711712	0.543478
Detection Rate	0.9780	0.001691	0.001605
Kappa:			0.265

From the perspective of sensitivity and precision statistics, XGBoost result shows better prediction on the risk of bank failure than the risk of bank takeover. Among all the banks which are seen to be failed from the actual data, 38% are also predicted to be failed. Among all the banks which are observed to be taken over from the actual data, 10% are predicted to be taken over. 71% of predicted failed banks are actual failures while 54% of predicted acquired banks are actual acquired banks. The detection rates are in a similar range for both risks. Overall, using XGBoost to fit the whole data gives notably better prediction than just random guess with Kappa value of 0.265.

As the model interpretation is not generally based on the parameter estimation from a machine learning model, other measures can be evaluated to get some takeaways from understanding the black box models. Feature importance is one main measure to interpret the model. The feature importance focuses on finding the variable rankings based on its contribution in the construction of the boosted decision trees. To be specific, the more loss reduction contributed from a variable which is used in the tree splitting, the higher feature importance it has for the model. It is a measure which can be used to compare relative importance among all the features in the model. Figure 3.2 shows the model feature importance result from XGBoost method using the whole data.

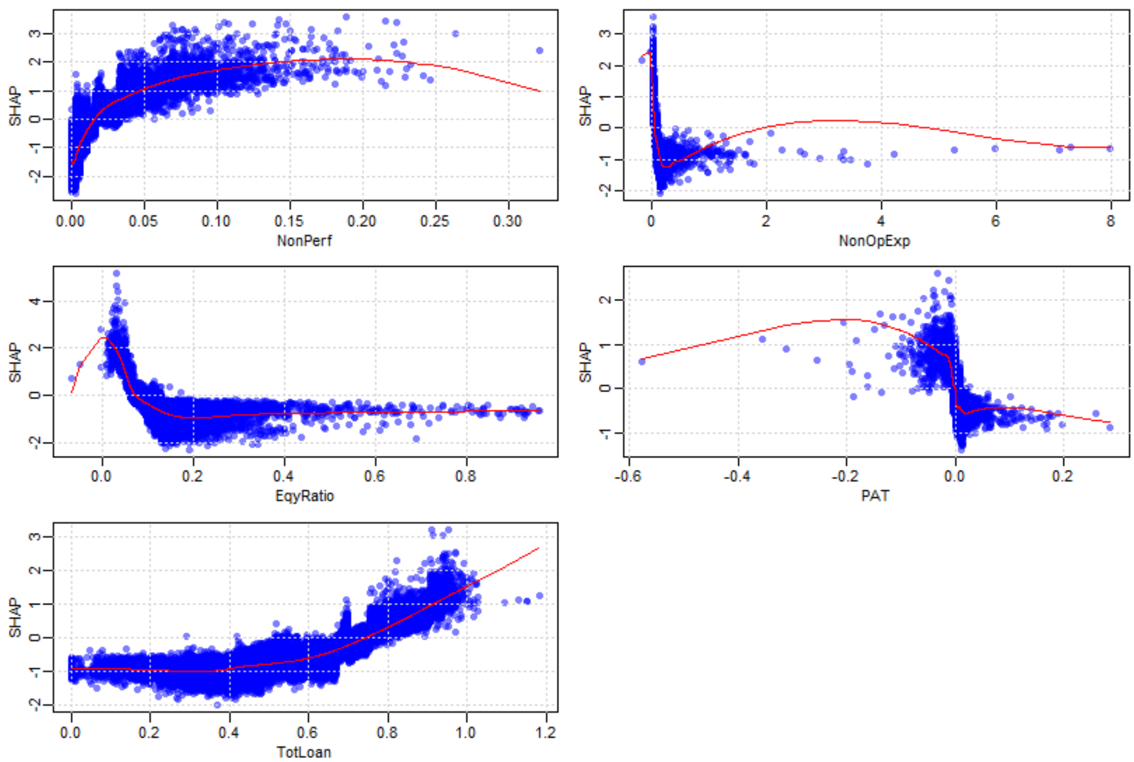
Figure 3.2: Variable Importance - XGBoost Method - Whole Data



It can be seen that the top five features from XGBoost method are non-operating expense ratio, net after tax income ratio, non-performing asset ratio, operating profit and equity ratio, while the least important feature is the indicator of whether the bank has foreign deposits or not.

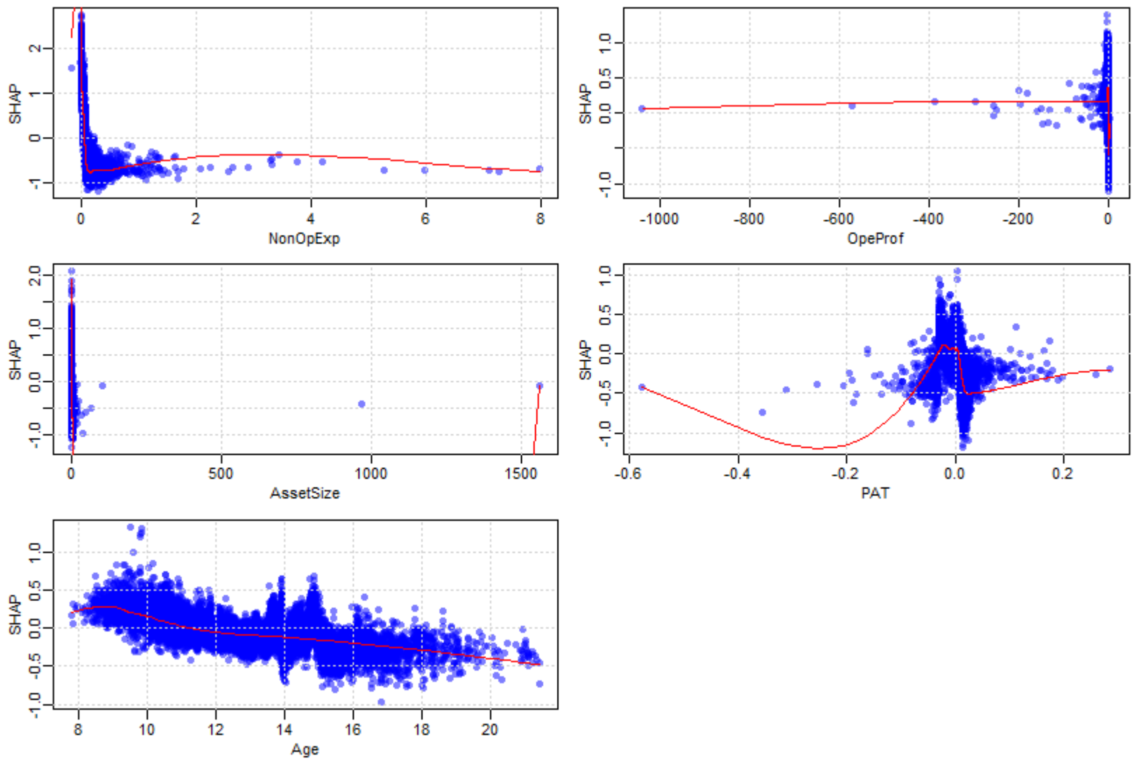
Besides feature importance, the SHAP values of the five top variables are examined for the risks of bank failure and bank takeover respectively under the analysis of using the whole data. Figure 3.3 and Figure 3.4 present the SHAP value examination for the two risks respectively.

Figure 3.3: SHAP Value of Bank failure Risk - XGBoost Method - Whole Data



SHAP value considers all the features impacting the final prediction in a collective way. For instance, to determine how much equity ratio impacts the probability of bank failure, it cannot be determined by treating all other features independently, or just taking out equity ratio while keeping the other features in the same order. SHAP value has considered all the combinations and the orders of features and decided the

Figure 3.4: SHAP Value of Risk Bank takeover - XGBoost Method - Whole Data



marginal impact from with and without of the feature. It gives comprehensive way to understand how each feature affects the targeted output. For the risk of bank failure, the most important five features are non-performing asset ratio, non-operating expense ratio, equity ratio, net after tax income ratio and total loans ratio. The SHAP value graph for each feature shows how the change of the feature value contributes to the predicted odds ratio of the risk. For the feature of the non-performing asset ratio, when it increases from the value of zero, its contribution to the risk of bank failure increases starting from a negative value, and the contribution increases at a slower rate when the non-performing asset ratio is getting larger. When non-performing asset ratio is larger than approximately 0.015, its contribution to the failure risk becomes positive, and when the non-performing asset ratio reaches to the value of around 0.20, the graph shows the contribution stops rising and it starts to decrease but still be kept as positive. For the feature of non-operating expense ratio, its contribution to the log odds of bank failure starts high at positive values when it is small. When non-operating expense ratio gets larger, its contribution drops fast at first and breaks the zero boundary to negative, then soon starts to increase to a peak when non-operating expense reaches to 3, and after then the contribution has a long but moderate decrease in the negative zone. For the feature of equity ratio, when it increases from zero, its contribution to the log odds bank failure risk starts in positive zone and decreases at a faster speed when the feature value is small than big. When the equity ratio is bigger than 0.08, its contribution to the failed risk becomes negative, and when it is over 0.18, its contribution to the failed risk stays stable at a negative value. For the feature net after tax income ratio, when it increases in the range between -0.2 and 0.2, its contribution to this failure risk decreases from a positive value to a negative value. For the feature total loans ratio, it sees an increasing contribution to the risk of bank failure when it increases, but the speed of the incremental is getting larger and larger when the feature value increases. When the total loans ratio is smaller than approximately 0.75, its contribution to the failed risk is negative, while when it is bigger than 0.75 this contribution becomes to be positive.

For the risk of bank takeover, the top 5 important variables are slightly different from the ones for risk of bank failure. Like the risk of bank failure, top 5 important variables have non-operating expense ratio and net after tax income ratio. Their contributions to the log odds of bank takeover is of similar pattern as to the risk event of bank failure. The other three top five important features are operating profit ratio, asset size and bank age. For the features of operating profit ratio and asset size, the majority observations are in a small range and when they increase, their contributions to log odds of bank takeover decrease when the values increase during the small range, and the contributions range from positive to negative. For the feature age, as it increases, its contribution to the log odds of bank takeover decreases in a stable speed from positive values to negative values.

3.4.2.3 Results Comparison From Two Methods - Whole data

From the perspective of the prediction performance accuracy, it shows XGBoost method produces better performance than traditional multinomial logistic regression using whole data. Both sensitivity and precision statistics are higher from XGBoost method than multinomial logistic regression method. The Kappa value of XGBoost method (0.265) is also significantly bigger than the one of multinomial logistic regression (0.122). From the perspective of feature importance, the two methods show similarity on the top 5 important variables as they have 4 overlaps. The four overlaps are non-operating expense ratio, net after tax income ratio, equity ratio and non-performing asset ratio. The remaining one different feature is delinquent asset ratio for multinomial logistic regression method, and age for XGBoost machine method. From the perspective of parameter specification, multinomial logistic regression assumes linear relationship between each feature and the log odds of the risk event relative the baseline state. For XGBoost machine learning method, the SHAP value analysis of top 5 important features for each risk (bank failure or bank takeover) exhibits that the important 5 variables can be different to some extent. The two risks have two overlaps in the top 5 important variables from each risk category. The SHAP value graphs show that the relationship between the feature and the contribution to log odds of risk event is not necessarily linear. For instance, non-performing asset ratio contributes to the risk of bank failure in a non-linear way. The SHAP values also range from positive to negative for each feature, thus it reflects more flexibility of how the feature contributes to the risks from machine learning model of XGBoost. The leverage of non-linear relationship between features and targeted variable is an advantage of machine learning model to improve the performance.

3.4.3 Results - Hold-out Data

The analysis in this section differs from the analysis using whole data in the way that it only uses part of the data which spans from 2002 to 2010 (in-sample data) to develop the model, and the performance is evaluated based on the model prediction on the data between 2011 and 2014 (out-of-sample data). In this way, it can simulate the real model prediction practice, as the out-of-sample prediction accuracy is more important for the generalization of model usage.

3.4.3.1 Multinomial Logistic Method - Hold-out Data

Table 3.8 shows the multinomial logistic model parameter estimates using data from 2002 to 2010. In this hold-out data analysis, although the magnitude of the parameter estimates for the development data is different from the estimates using whole data, the estimates show same directions from all the independent variables on the two risks compared with using whole period data except two variables. Specifically, the parameter estimates of non-performing asset ratio on the risk of bank takeover and asset size on the risk of bank failure exhibit different signs between using whole data and using data spans from 2002 to 2010.

Table 3.8: Parameter Estimates - Multinomial Logistic Method - Hold-out Data

	Dependent variable:	
	Failure	Takeover
EquityRatio	-29.156^{***}	-7.083^{***}
	(0.0001)	(0.0001)
TotalLoan	4.527^{***}	0.542^{***}
	(0.001)	(0.001)
ReLoan	1.662^{***}	0.606^{***}
	(0.002)	(0.001)
CniLoan	2.334^{***}	1.068^{***}
	(0.0003)	(0.0004)
OtherRe	20.309^{***}	-6.271^{***}

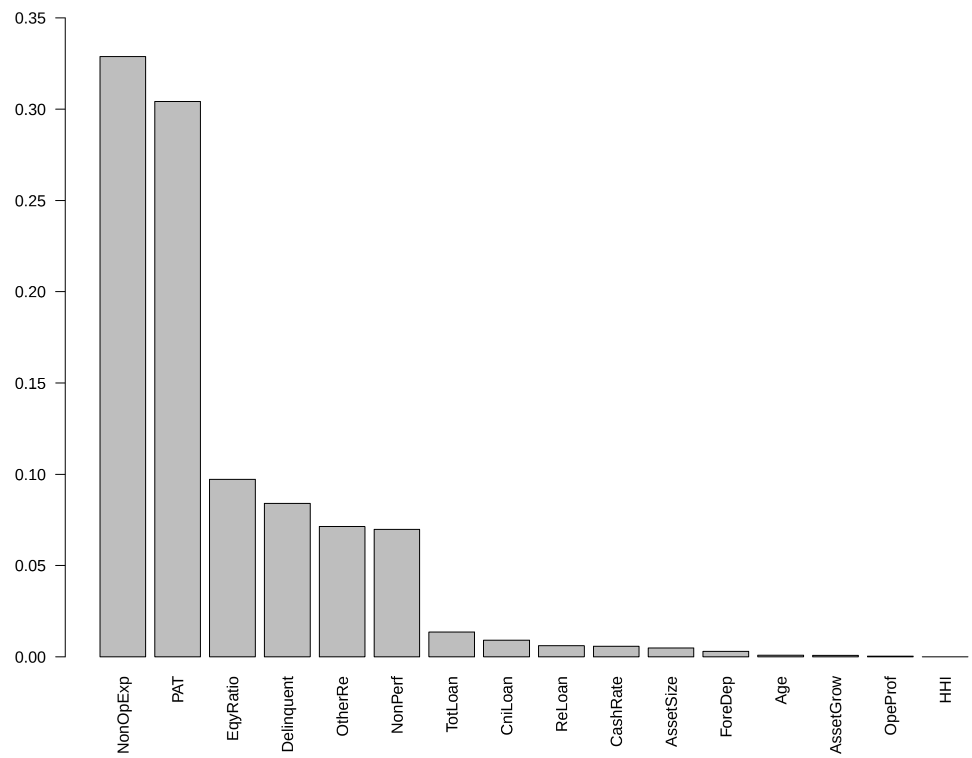
Table 3.8: (continued)

	Dependent variable:	
	Failure	Takeover
	(0.0001)	(0.00001)
Delinquent	27.897***	−3.409***
	(0.00004)	(0.00002)
NonPerforming	24.821***	−1.192***
	(0.0002)	(0.00004)
NonOperatingExp	−63.315***	−59.206***
	(0.0001)	(0.0001)
PAT	−53.089***	−60.265***
	(0.0001)	(0.00005)
OperatingProfit	−0.082***	−0.058***
	(0.006)	(0.004)
CashRate	0.365***	1.788***
	(0.0001)	(0.00002)
Age	−0.103*	−0.184***
	(0.054)	(0.026)
AssetSize	−0.039**	−0.293***
	(0.016)	(0.009)
AssetGrowth	−0.286***	−1.525***
	(0.004)	(0.002)
HHI	0.00000	0.0001***
	(0.00003)	(0.00001)
ForeignDepositFlag	−0.831***	−0.274***
	(0.001)	(0.0003)
Constant	−3.589***	3.528***
	(0.001)	(0.0004)

Note: *p<0.1; **p<0.05; ***p<0.01
The value in parenthesis is the feature's standard deviation

Besides parameter estimates for the features, the feature importance is examined on the model built on the data which only spans from 2002 to 2010. Figure 3.5 shows the variable importance result for this development data. It can be seen that the top important five features are non-operating expense ratio, net after tax income rate, equity ratio, delinquent asset ratio and other real estate owned ratio. The top 5 features are mostly aligned with the results using whole data, with only the rankings change between net after tax income ratio and non-operating expense ratio, and having other real estate owned ratio as the fifth important variable than the non-performing loan ratio.

Figure 3.5: Variable Importance - Multinomial Logistic Method - Hold-out Data



The performance accuracy is evaluated on the out-of-sample data, which is from 2011 to 2014. Table 3.9 shows the confusion matrix on the out-of-sample data using multinomial logistic regression method, while Table 3.10 shows the major statistics on the confusion matrix.

Overall, the out of sample prediction statistics are similar with the ones from using whole data set. Kappa value of 0.134 implies the prediction is notably different from just random guess. It also shows the regression prediction works better on the risk of bank failure compared to the risk event of bank takeover. In all the observed bank failures, 59% are predicted to fail, while in all the observed banks which are acquired, only 0.9% are predicted to be acquired. Although the precision of bank takeover exhibits higher value (62%) than the bank failure (35%), the total predicted acquired cases of 8 are much less than the total predicted failed cases of 127. Multinomial logistic regression predicted more failed banks than acquired banks, while in actual data there are more acquired banks than failed banks. In sum, the model performs better on the risk of bank failure than the risk of bank takeover.

Table 3.9: Confusion Matrix - Multinomial Logistic Method- Hold-out Data

		Actual Value			
		Base	Failure	Takeover	Total
Predicted Value	Base	25171	28	570	25769
	Failure	73	44	10	127
	Takeover	1	2	5	8
	Total	25245	74	585	25904

Table 3.10: Selected Statistics - Multinomial Logistic Method - Hold-out Data

	Base	Failure	Takeover
Sensitivity	0.99707	0.594595	0.0085470
Precision	0.97679	0.346457	0.6250000
Detection Rate	0.97170	0.001699	0.0001930
Kappa:			0.134

Overall, the out of sample prediction statistics are similar with the ones from using whole data set. Kappa value of 0.134 implies the prediction is notably different from just random guess. It also shows the regression prediction works better on the risk of bank failure compared to the risk event of bank takeover. In all the observed failed banks, 59% are predicted to be failed, while in all the observed banks which are acquired, only 0.9% are predicted to be acquired. Although the precision of bank takeover exhibits higher value (62%) than the bank failure (35%), the total predicted acquired cases of 8 are much less than the total predicted failed cases of 127. Multinomial logistic regression predicted more failed banks than acquired banks, while in actual data there are more acquired banks than failed banks. In sum, the model performs better on the risk of bank failure than the risk of bank takeover.

3.4.3.2 Machine Learning Model - Hold-out Data

This section presents the results for machine learning model of XGBoost method. Like in multinomial logistic regression, it uses XGBoost machine to learn the data from 2002 to 2010 (in-sample data), and then predicts the performance on the out of sample data from 2011 to 2014 (out-of-sample data) for the bank risks of failure and takeover. Table 3.11 shows the confusion matrix for the out of sample data and Table 3.12 summarizes major statistics from the confusion matrix using XGBoost method.

Table 3.11: Confusion Matrix - XGBoost Method- Hold-out Data

		Actual Value			
		Base	Failure	Takeover	Total
Predicted Value	Base	24346	29	480	24855
	Failure	100	42	18	160
	Takeover	799	3	87	889
	Total	25245	74	585	25904

Table 3.12: Selected Statistics - XGBoost Method - Hold-out Data

	Base	Failure	Takeover
Sensitivity	0.9644	0.567568	0.148718
Precision	0.9795	0.262500	0.097863
Detection Rate	0.9399	0.001621	0.003359
Kappa:			0.140

The XGBoost model predicted accuracy on the out-of-sample data shows that it is notably better than random guess with Kappa value of 0.14. The Kappa value drops compared to the one from using whole data. It is reasonable as using whole data utilizes all the data information, which can give better prediction accuracy than the practice of evaluating performance accuracy on out-of-sample data while this part of data information is not considered in the model development. It also reflects machine learning model is relatively more subjected to overfitting than using parametric statistic technique. It shows the model works better in predicting the risk of bank failure than the risk of bank takeover. Among the actual observed failed banks, 57% of them are predicted to be failed. Among the actual observed acquired banks, around 15 % of them are predicted to be acquired. The precision shows that among all the predicted failed bank cases, 26% are real bank failures, while 10% of predicted acquired bank cases are real acquired bank cases. Although the model detects more acquired bank cases than failed bank cases (detection rate for bank takeover is 0.3% and detection rate for bank failure is 0.2%), the actual acquired bank cases are even more than actual failed bank cases (585 bank cases are actual acquired cases while 74 bank cases are actual failed cases).

Figure 3.6 shows variable importance from XGBoost method on the in-sample data. The top five important features are non-operating expense ratio, non-performing asset ratio, net after tax income ratio, operating profit ratio and equity ratio. The top five important features are same with using XGBoost method for the whole data, with just a ranking change between net after tax income ratio and non-performing asset ratio. Hence using development data of 2002 to 2010 shows stability compared with using whole data.

Figure 3.7 and Figure 3.8 show the SHAP value examination on the out-of-sample data from the top five important features which affects the risks of a particular risk event (bank failure and bank takeover respectively).

Figure 3.6: Variable Importance - XGBoost Method - Hold-out Data

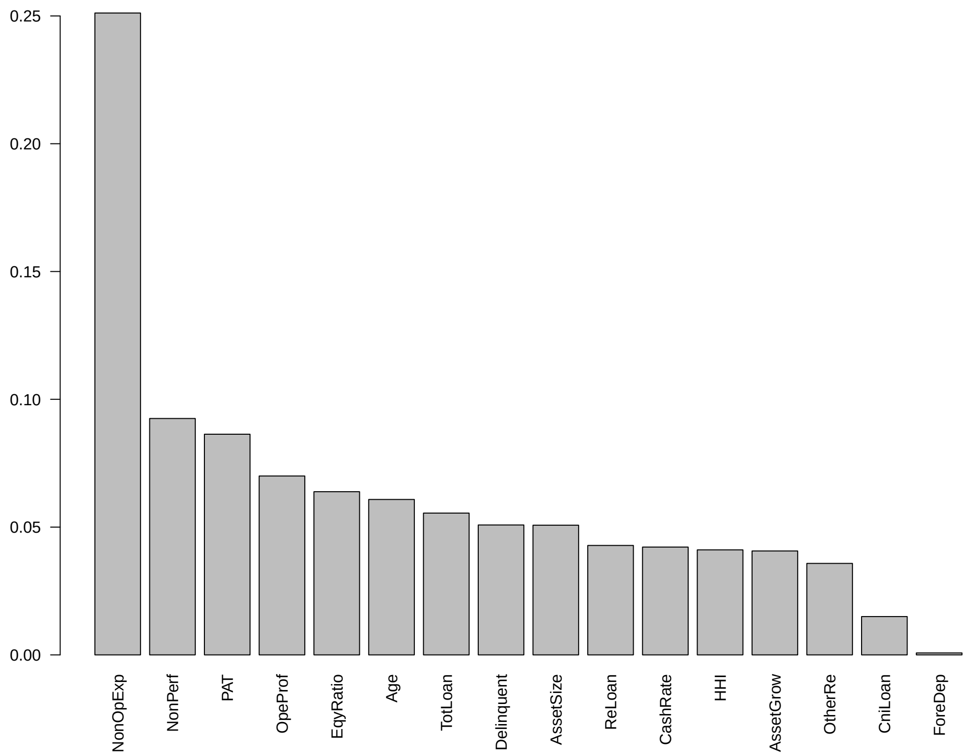


Figure 3.7: SHAP Value of Risk Bank Failure - XGBoost Method - Hold-out Data

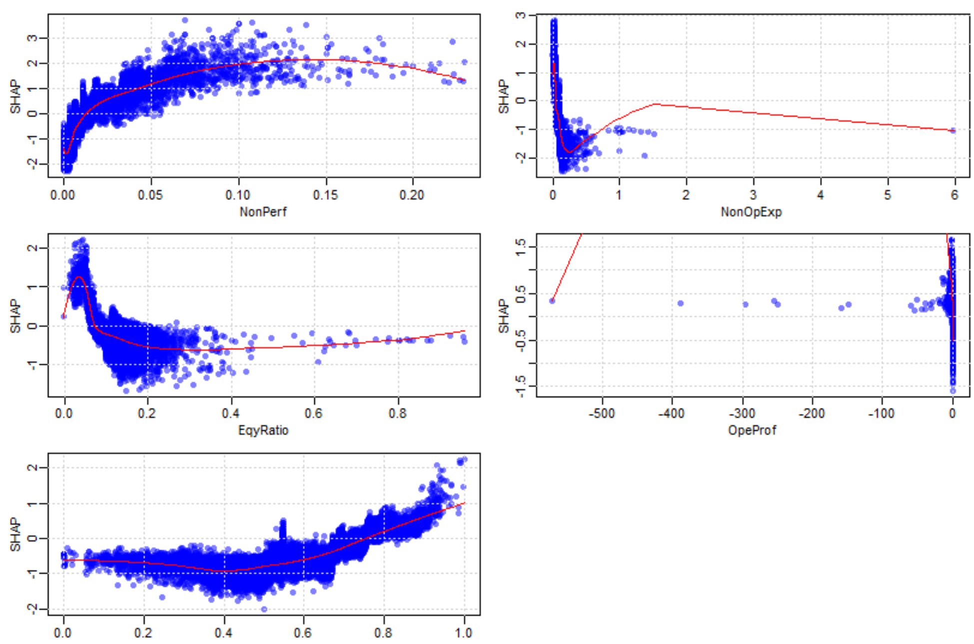
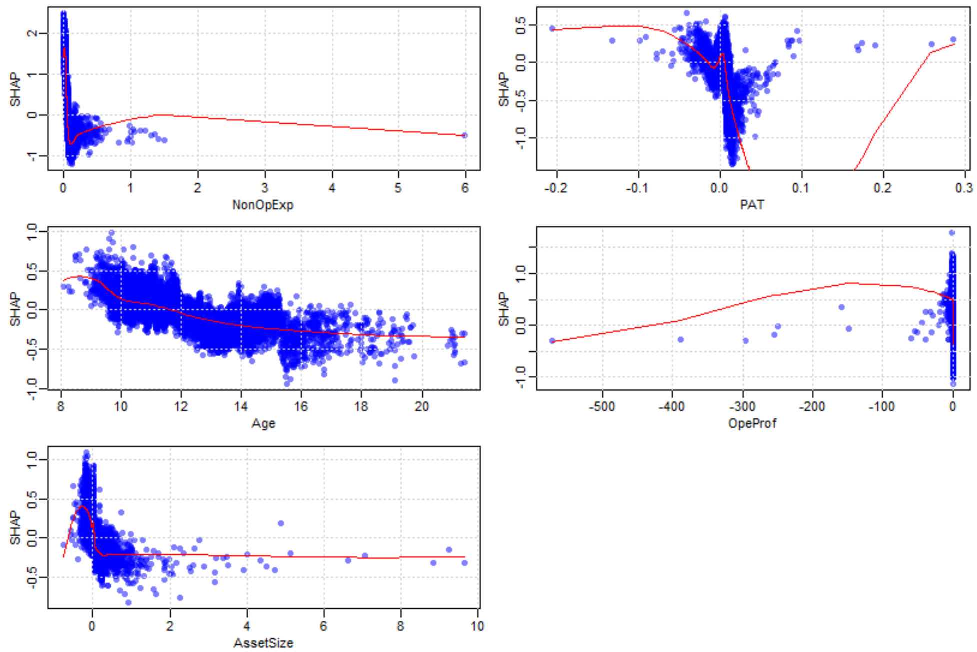


Figure 3.8: SHAP Value of Risk Bank takeover - XGBoost Method - Hold-out Data



For the risk of bank failure, the top five important features are similar to the ones from feature importance analysis result, except it swaps out the feature of net after tax income ratio and swaps in the feature of total loan ratio in the top 5 important features list from the SHAP value assessment. For the feature non-performing asset ratio, when it increases, its contribution to odds ratio of bank failure increases with slower speed when the feature goes bigger until around 0.13. After that point the odds ratio starts to go down when the feature value keeps increasing. Its contribution is negative when it is small and then goes beyond zero when it is bigger than 0.01. For the feature non-operating expense ratio, when it increases, its contribution to the odds ratio of bank failure initially decreases at a fast speed, and then goes up until some point around 1.5, then steadily goes down after that. The contribution from non-operating expense ratio to the bank failure risk is mostly negative. For the feature equity ratio, when it goes up, its contribution to the odds ratio of bank failure rises fast initially and then goes down till the equity ratio approaches to the value of around

0.22, and after that the contribution stays stable at a negative value. For the feature operating profit ratio, when it increases at the neighborhood of zero, its contribution to the odds ratio of bank failure decreases. For the feature total loan ratio, when it goes up from zero, its contribution to the odds ratio of bank failure decreases at a low speed initially till it reaches to the value of 0.4, then the contribution increases and breaks zero to become positive when the feature goes closer to 0.8. In sum, all the most important five features show non-linear contribution to the risk of bank failure, and the contribution from each variable can be both positive and negative.

For the risk of bank takeover, the top five features are non-operating expense ratio, net after tax income ratio, age, operating profit ratio and asset size. Compared to the risk of bank failure, risk of bank takeover has two same features (non-operating expense ratio and operating profit ratio) on the top 5 important features list with the risk of bank failure. The two common features show similar contribution patterns to the odds ratio of the two risks. Among the other three features, they also show non-linear relationships on the contribution to odds ratio of the bank takeover to some extent. For the features of net after tax income ratio and asset size, the majority observations are in a small range and when they increase, their contributions to log odds of bank takeover decrease. Also when the feature values increase during the small range, the incremental sometimes changes directions. For the feature age, as it increases, its contribution to the log odds of bank takeover decreases from positive values to negative values in a stable speed, which means when the bank is young it is more likely to be taken over but when the bank is getting old it is less likely to be taken over.

3.4.3.3 Results Comparison From Two Methods - Hold-out Data

From the perspective of the prediction accuracy on the out-of-sample data, both multinomial logistic regression method and XGBoost method exhibit better performance than just random guess. The Kappa values of the two methods are similar. In terms of sensitivity, relative to the actual observed risk events, XGBoost method predicts more accurate banks takeover (15%) than using multinomial logistic regression (0.9%), while the two methods both predict similar percentages of accurate bank failures relative to observed bank failure cases. In terms of precision, although multinomial logistic method produces higher precision statistics for both failed and acquired risks than using XGBoost method, XGBoost method predicts more failed cases as well as acquired cases. It also means that the XGBoost method predicts more false acquired banks than multinomial logistic regression. In terms of feature importance analysis, both methods produce the similar top five important features using development data compared to using whole data. The model parameter specification for the multinomial logistic regression, as well as the SHAP value analysis for the XGBoost method, are also discussed for the hold-out data prediction practice. Overall, the machine learning models can capture non-linear relationship between features and the contribution to the targets of odds ratio, which cannot be realized in multinomial logistic regression.

3.5 Conclusion

This paper uses both traditional multinomial logistic regression and the machine learning method of XGBoost to see the impacts of different financial ratios and some bank specific features on the US bank risks of failure or takeover. It compares the two methodologies in terms of model accuracy and feature importance rankings. In addition, the parameter specification for multinomial logistic regression and SHAP value analysis for XGBoost are also examined.

The analysis is conducted in two ways. First, I use the full data to build the models and the evaluation is also on the full data. The results show the machine learning XGBoost method has better prediction accuracy than multinomial logistic regression in terms of Kappa statistic. The two methods exhibit large similarity in their measure of feature importance as there are 4 overlapped features (after tax profit ratio, non-operating expense ratio, equity ratio and non-performing loan ratio) among the top 5 important features. The multinomial logistic regression assumes each feature exhibits a linear relationship with the odds ratio of each risk. From the SHAP value analysis for the XGBoost method, it can be seen that the top features can vary for different risks. In addition, the predicted relationship between each feature and targeted odds risk ratio can be clearly seen to be non-linear, and the contribution from feature to the targets can even change signs. The non-linearity of the machine learning model gives large flexibility and makes it ccbetter performed than traditional multinomial logistic regression modeling method.

Second, this paper uses in-sample data which spans from 2002 to 2010 to build the model, and the evaluation of prediction accuracy is based on out-of-sample data which spans from 2011 to 2014. This analysis simulates real prediction practice. Both methods are statistically noticeably better than a random guess. The outperformance of XGBoost method is not obvious under this practice. The prediction accuracy is relatively stable using multinomial logistic regression method compared with the result from the first practice (develop and evaluate using whole data), while the prediction accuracy drops using XGBoost method compared with the first practice. It may imply the machine learning method is more subject to overfitting the development data. To be specific, under XGBoost method the model is chosen to fit the development data (2002 to 2010) and ensure high performance accuracy for the same data. Although the model is chosen to avoid overfitting in the development data, it doesn't ensure to avoid overfitting for predicting in the out-of-sample data. Given the result provides the evidence that the machine learning model prediction performance may not be as stable as multinomial logistic regression method, it may imply the direction for the future research on deep dive into the reason why the prediction accuracy drops significantly using machine learning. Between the two risks of bank failure and bank takeover, both multinomial logistic regression method and XGBoost method can give better prediction accuracy on the risk of bank failure than the risk of bank takeover. The two methods exhibit large similarity in their measure of feature importance as there are 3 overlapped features (non-operating expense ratio, after tax profit ratio and equity ratio) among the top 5 important features. The way each feature contributes to bank failure and bank takeover can be of different weights. Again, the SHAP value analysis for the XGBoost method displays the flexibility each feature contributing to the risks in terms of magnitude and direction.

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Appendix A

IMPACT OF BANK ACQUISITION ON THE ACQUIRING BANK IN THE U.S.

A.1

Supporting Summaries

Table A.1 shows the financial ratios summary statistics for all the banks in the periods when they don't conduct mergers and acquisitions. They are in percentage unit except for profit per employee which is in terms of dollar value.

Table A.1: Financial Variables Summary Statistics - Other Banks

Target	Mean	St. Dev.	Min	Max
EquityRatio	10.9	4.1	−9.6	96.1
TotalLoan	63.5	15.8	0	118.3
ReLoan	69.1	19.5	0	102.8
CniLoan	3.5	8.3	0	100
OtherRe	0.5	1.2	0	30.6
Delinquent	0.8	0.8	0	17.2
NonPerforming	1.1	1.8	0	40.7
NonOperatingExp	7.4	7.5	−3.3	798
ProfitPerEmployee	244	11,113	−47,328	1,729,752
ROE	19.1	128.1	−891	3,059

Table A.1: (continued)

Target	Mean	St. Dev.	Min	Max
OperatingProfit	1.1	507.6	−1,040	563.6
CashRate	1.5	5.9	−85.4	92

A.2

More Merger and Acquisition Impact Figures

Figure A.1 to Figure A.10 display more merger and acquisition impact results on the performance measures (which display significant acquisition impacts) from group time difference-in-difference methodology.

Figure A.1: Equity Ratio Results - During-Credit Crisis

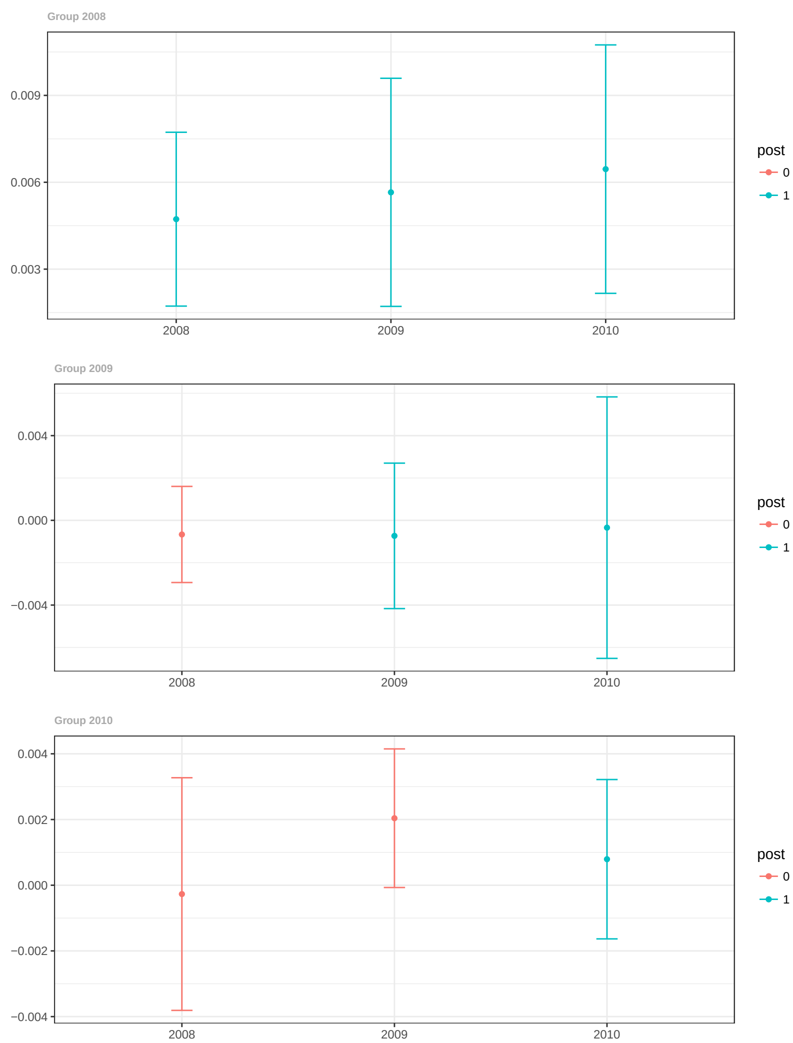

Figure A.2: Commercial and Industrial Loan Results - During-Credit Crisis

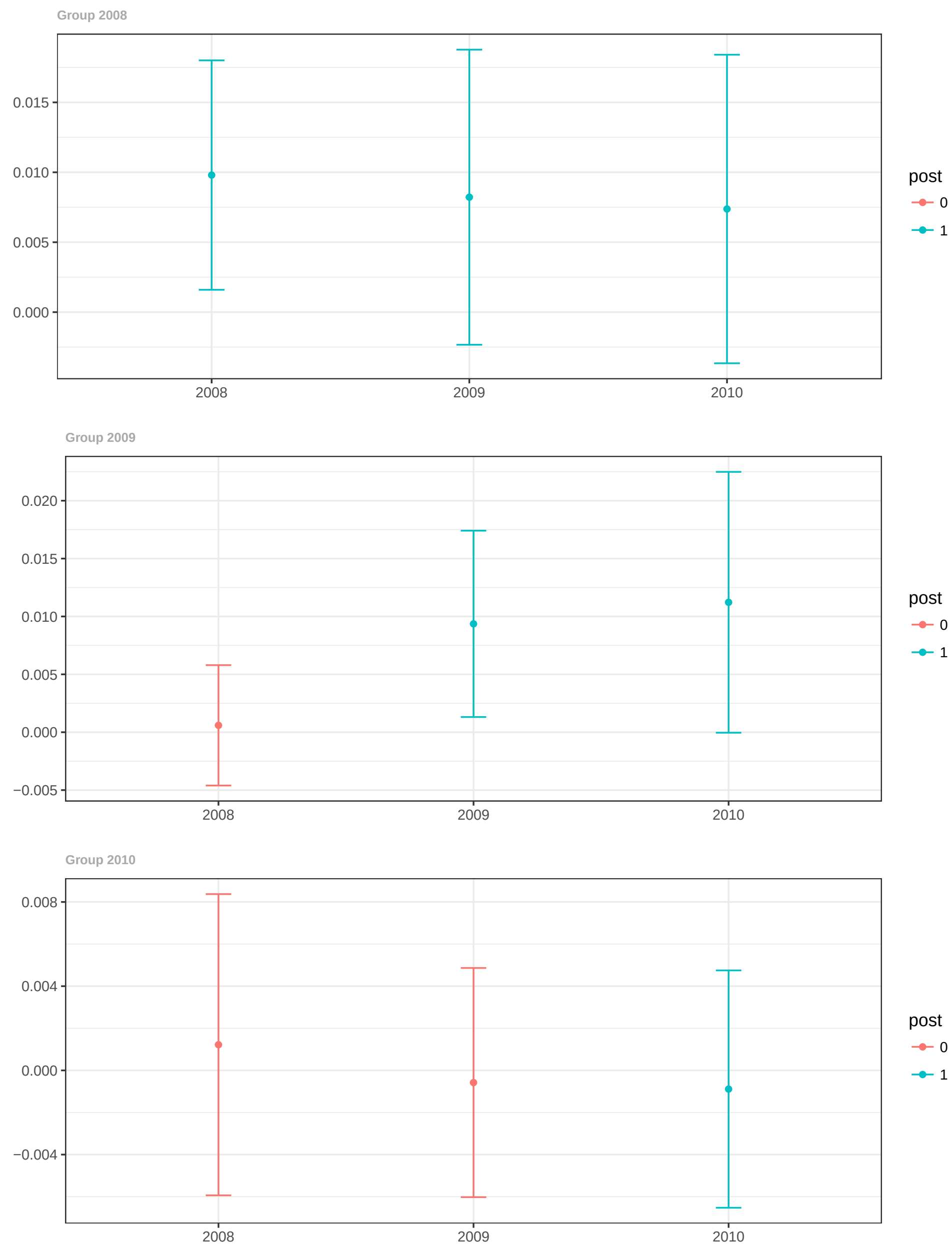

Figure A.3: Delinquent Assets Results - During-Credit Crisis

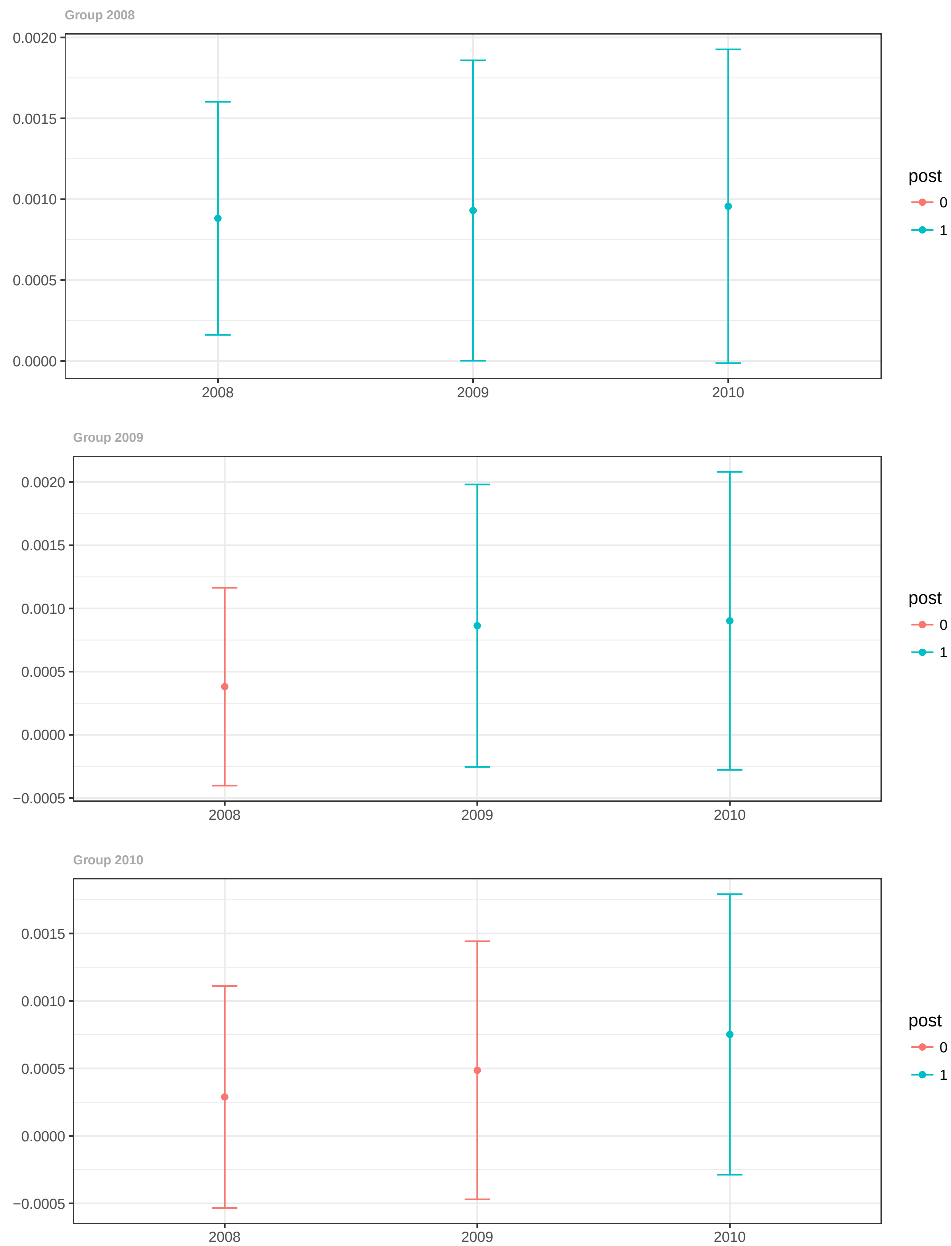

Figure A.4: Non Performing Assets Results - During-Credit Crisis

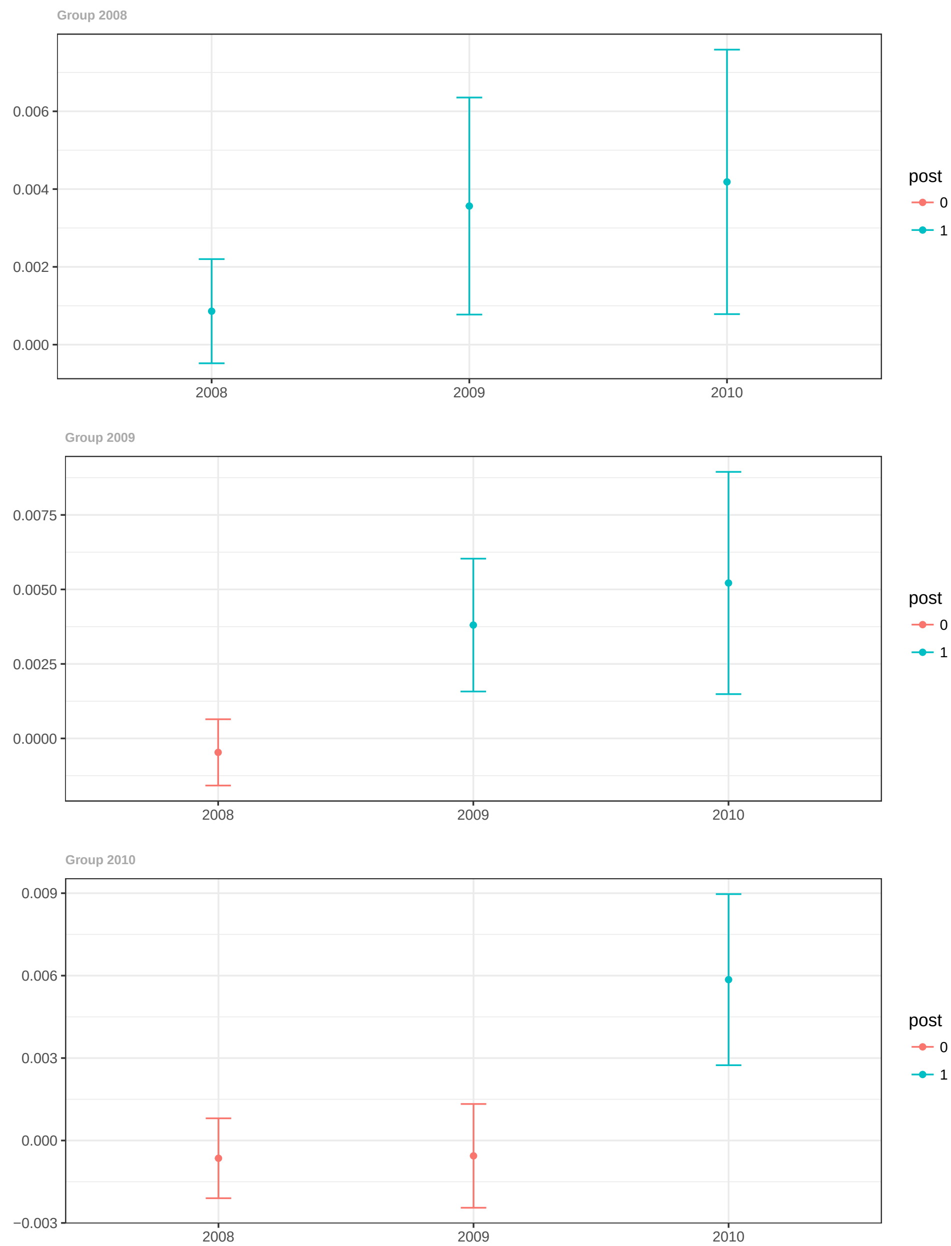

Figure A.5: Return on Equity Results - During-Credit Crisis

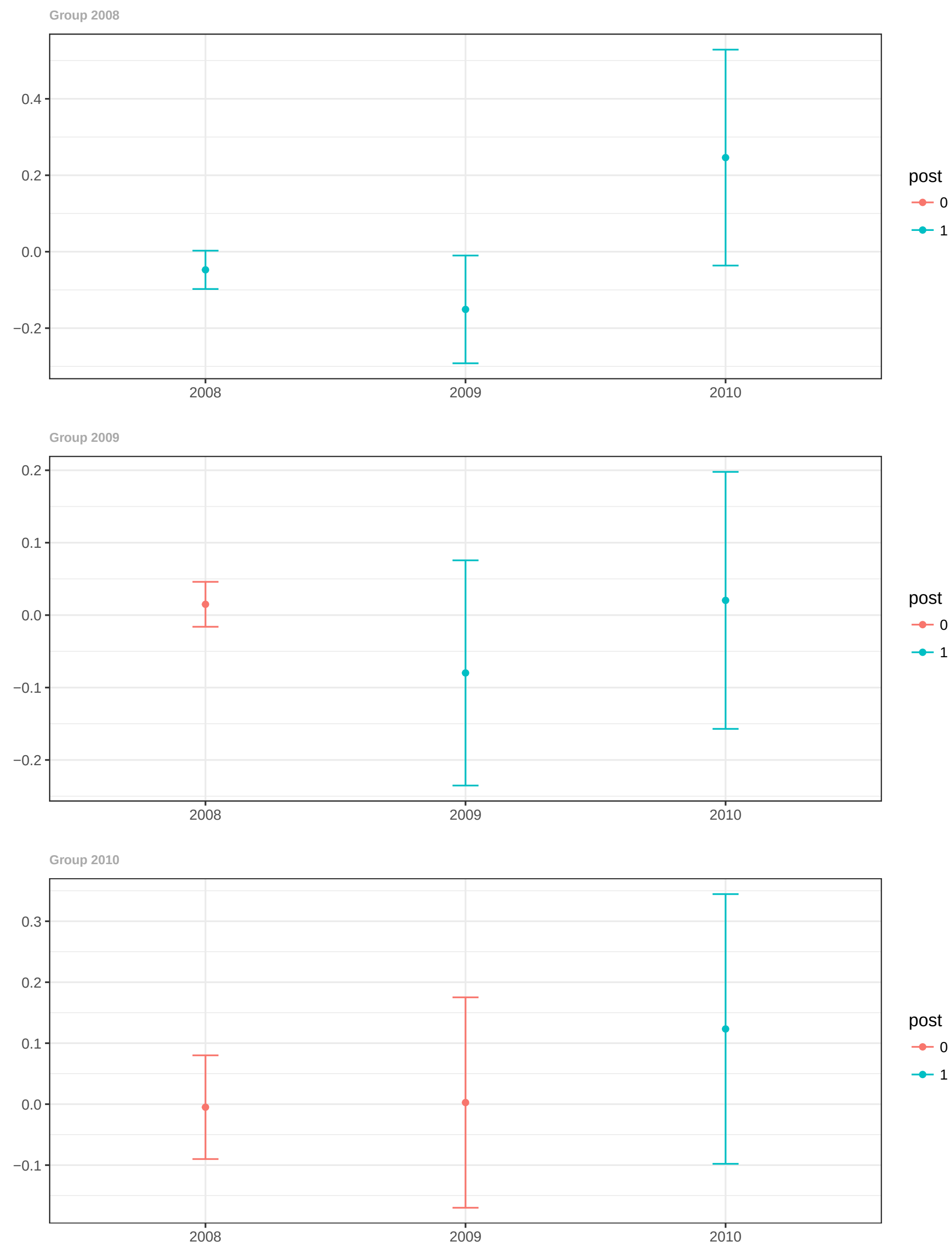

Figure A.6: Commercial and Industrial Loan Results - Post-Credit Crisis

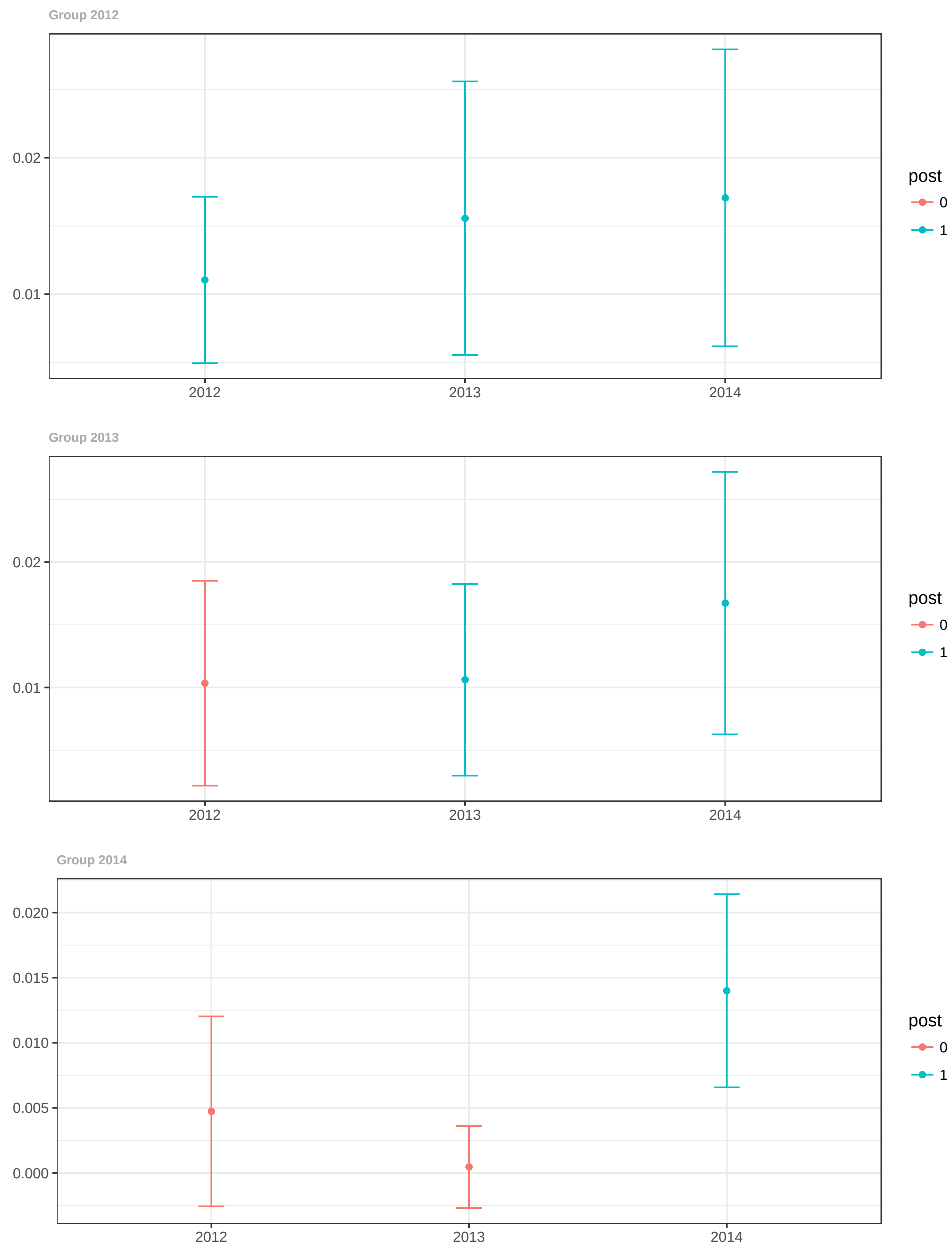

Figure A.7: Delinquent Assets Results - Post-Credit Crisis

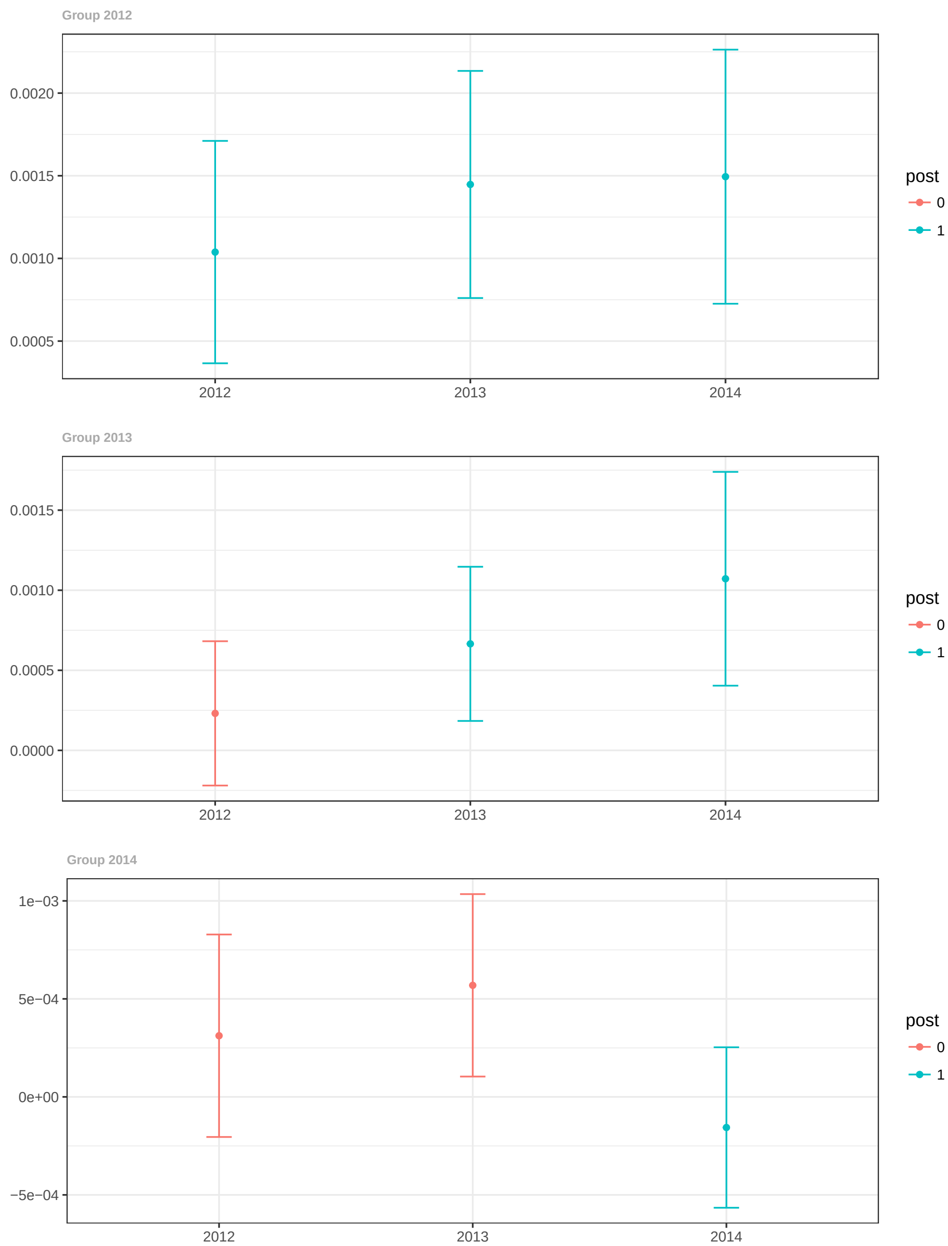

Figure A.8: Non Performing Assets Results - Post-Credit Crisis

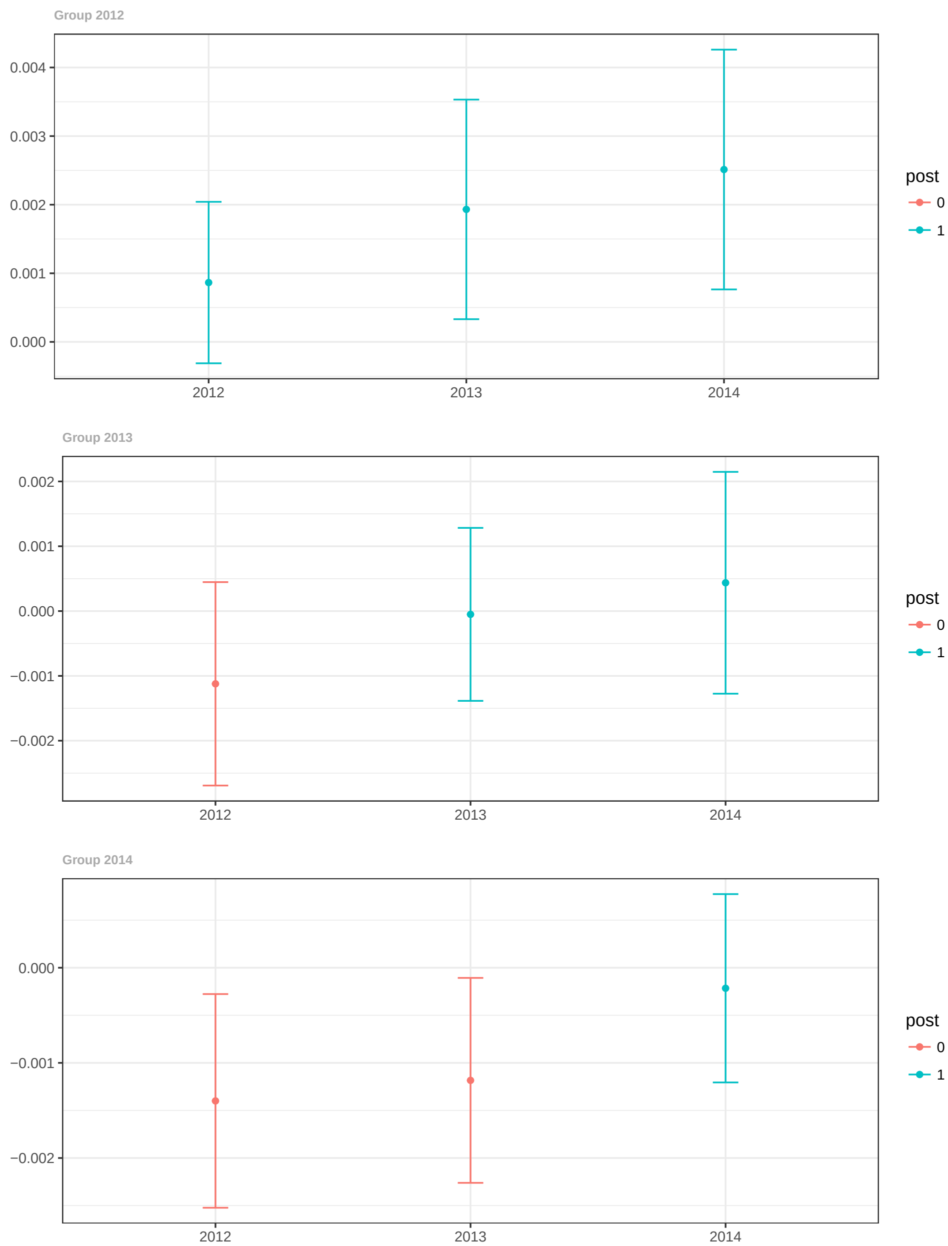

Figure A.9: Return on Equity Results - Post-Credit Crisis

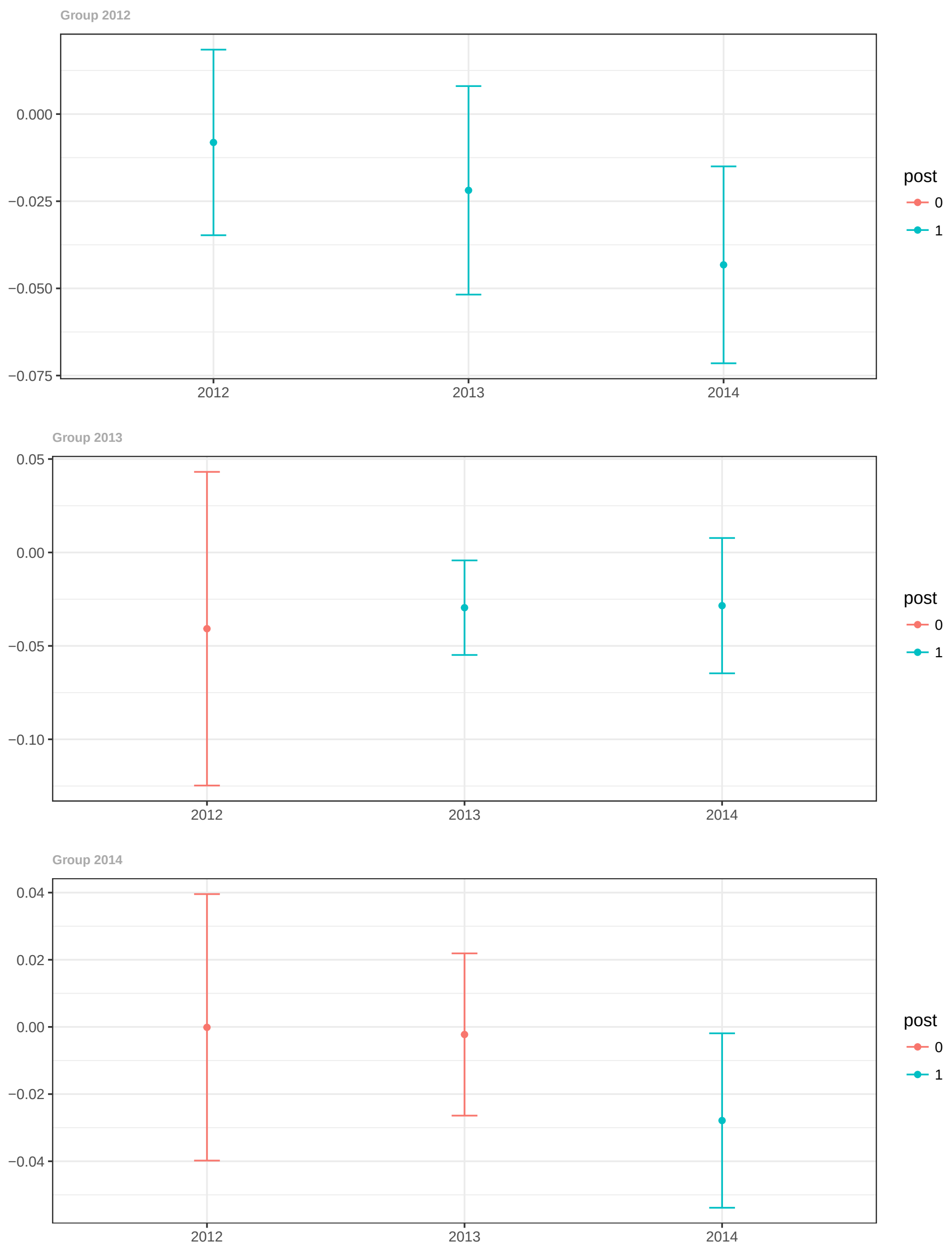

Figure A.10: Cash Rate Results - Post-Credit Crisis