Impacts of the Dodd-Frank Wall Street Reform and Consumer Protection Act on the Consolidation of the U.S. Banking Industry

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Senior Honors Thesis

Spring 2019 Final Draft

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1. Introduction

This paper seeks to contribute to the literature exploring the consolidation of the U.S. banking industry by examining changes in the characteristics of merger and acquisition activity in the United States banking industry in the wake of the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act. The current era of banking consolidation in the United States began in 1985, but many critics of the Dodd-Frank Act, which was enacted in the wake of the 2007 financial crisis, have argued for years that the law is a driving force behind current consolidation trends. The law's opponents decry it as government oversight gone too far, suggesting that the costs associated with Dodd-Frank drive otherwise healthy community banks out of the market, weaken the financial system, and misallocate resources (Hensarling 2015, Lux and Greene 2016). This argument has proven so persuasive that in May of 2018, Congress passed the Economic Growth, Regulatory Relief and Consumer Protection Act, which weakened numerous tenets of Dodd-Frank in the hopes of lessening the regulatory burden of the law. The fact that Congress is creating policy based on the theory that the Dodd-Frank Act promotes consolidation in the banking industry creates a pressing need for literature that explores that very topic.

This paper makes two distinct contributions. First, it provides a descriptive analysis of the factors that predicted a bank's exit from the market through merger or acquisition in the periods before and after the passage of the Dodd-Frank Act, stratified by community bank status. This analysis shows very few changes in the characteristics of merging or acquired banks from the pre- to the post-Dodd-Frank periods, suggesting that consolidation trends today are no more harmful than they were in the era before the law was passed. What changes I do find, namely that merged banks in the post-Dodd-Frank period were less profitable and had lower yield on earning assets relative to their peers than in the pre-Dodd-Frank period, suggest that any changes in consolidation trends only impacted the weakest banks. Consolidation trends are of course subject to numerous forces besides the law, so this paper makes no causal claim regarding the impact of the Dodd-Frank Act on broad trends in the factors that predict consolidation. Nevertheless, it offers insight into the general direction of consolidation trends during the years in which Dodd-Frank has been in effect. Second, this paper uses a differences-in-differences model to determine whether three significant regulatory thresholds created by the Dodd-Frank Act, which impose additional regulatory burden on banks with more than $10 billion in assets, caused a significant slowdown in merger and acquisition activity by banks with between $5.5 and 8.5 billion in assets. The Dodd-Frank Act exempted banks with less than $10 billion in assets from regulation by the Consumer Financial Protection Bureau (CFPB), annual company-run stress tests, and the Durbin Amendment, which limits interchange fees on debit card transactions.[1] These regulations, particularly the former two, represent a significant cost to banks (Nicoletti et al. 2017). My differences-in-differences analysis compares banks in a range just below the regulatory threshold to their peers and suggests that banks with between $5.5 and 8.5 billion in assets limited their merger and acquisition activity in the post-Dodd-Frank period. This is in line with prior literature which suggests that firms will alter their behavior in order to avoid becoming subject to onerous additional regulatory burden (Onji 2009, Dharmapala 2016, St. Clair 2016). Overall, this paper provides very little evidence to support the idea that the Dodd-Frank Act has created or accelerated any harmful consolidation trends in the banking market, and in fact suggests that the Act may have slowed down consolidation activity among at least one specific subset of banks.

[1] Congress increased the threshold at which banks must carry out company-run stress tests from $10 billion to $250 billion in assets in May 2018 with the passage of S.2155, the Economic Growth, Regulatory Relief and Consumer Protection Act.

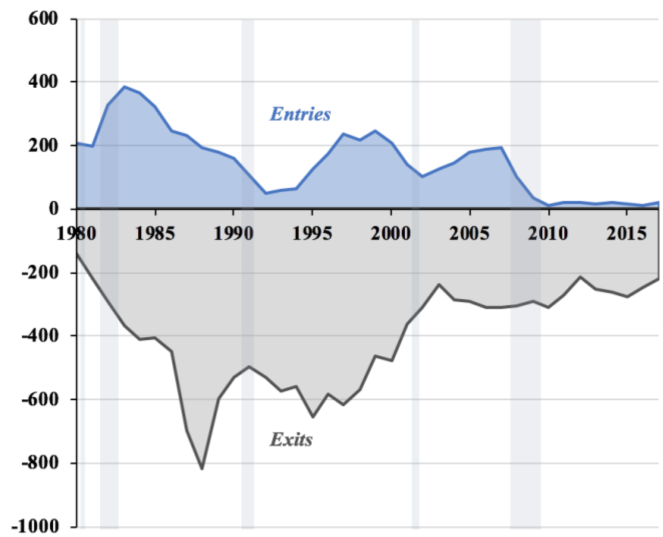
The rest of the paper is structured as follows: Section 2 contains an overview of relevant literature, Section 3 outlines the data I use in my analysis, Section 4 includes the empirical method and results of my descriptive analysis of the characteristics of merged and acquired banks in the pre- and post-Dodd-Frank periods, Section 5 explains the methodology and results of my differences-in-differences model, and Section 6 outlines my conclusion.

2. Literature Review

2.1 A Brief Overview of Consolidation of the U.S. Banking Industry

The U.S. banking industry has historically been characterized by the significant entries and exits of firms to and from the market. From 1933, when the Federal Deposit Insurance Corporation (FDIC) was established, until 1984, the number of banks in the U.S. never fell below 13,000. New bank formation prior to the 1980s was relatively pro-cyclical, with the number of new entries in a year ranging from 36 in 1942 to 370 in 1974. Bank closures were comparatively stable in number, ranging between 76 and 258 exits per year prior to 1980. For every year on record, the number of unassisted mergers has outstripped the number of bank failures. On average, unassisted mergers comprise more than 85 percent of exits from the market (FDIC 2018 and author's calculations). The vast majority of

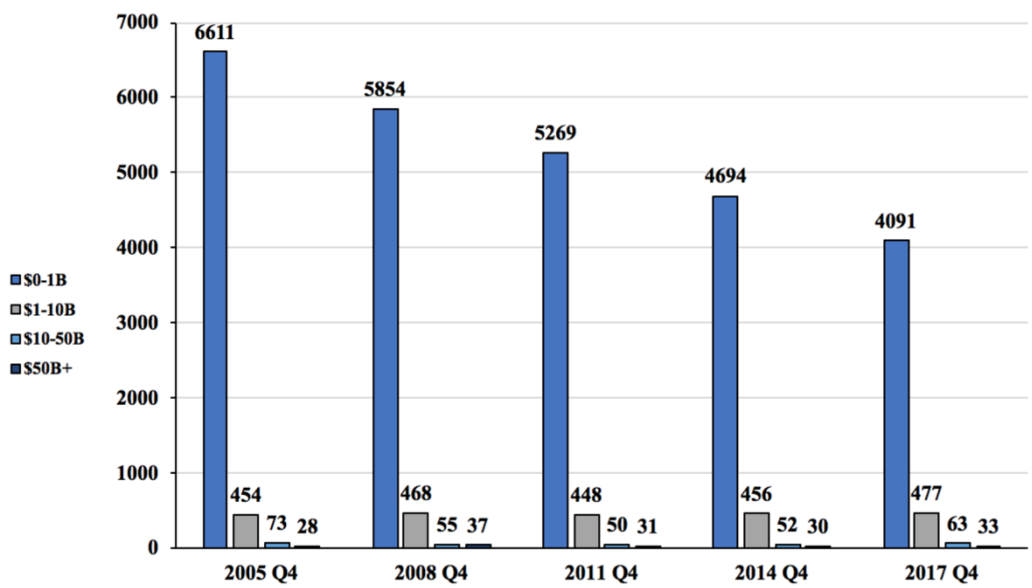
Figure 2.1: Annual Exits and Entries to the U.S. Banking Market
1980-2017



Shaded areas indicate U.S. recessions

banks that exit the market are small and community banks, and the average size of banks has risen (Hou and Warusawitharana 2018).

Figure 2.2: Number of Banks by Asset Size



For most of the period of consolidation that has occurred from 1985 to the present day, entry to the market has been healthy, and industry consolidation has been due almost entirely to an increased rate of exit. In 1985, when the current era of consolidation began, new bank entry was relatively high: 280 de novo charters were granted that year, and 356 new charters had been granted only the year before. However, these healthy rates of entry were outstripped by historically high rates of both mergers and failures. At the peak in 1988, 815 banks closed their doors.[2] Bank exits have not returned to pre-1980s levels. Since 2002, exits have fluctuated between 214 and 310 exits per year.

[2] This occurred at the height of the Savings and Loan crisis, frequently referred to as the S&L crisis, during which more than a thousand financial institutions failed. The vast majority of those failures were savings and loan associations. Of the 3,234 savings and loan institutions in the United States, 1,043 failed between 1986 and 1995. The failed institutions had combined assets over $500 billion (Curry and Shibut 2000). An average of 93 banks per year failed during this period, an unusually large number.

For much of the history of consolidation, researchers have examined whether economies of scale are a main driver of the increase in market concentration. Research from previous decades suggested that economies of scale did not exist in banking, or only existed for banks up to a relatively small size, and therefore mergers were harmful to consumers and often resulted in diseconomies of scale. Boyd and Graham (1991) concluded that banks only exhibited economies of scale up to the “relatively modest” size of $100 million, even finding that some of the largest banks, “in the multibillion dollar range,” exhibited diseconomies of scale, increasing their average production costs as they grew larger still. Other research found economies of scale only up to $500 million in assets, a size that is still moderately small (McAllister and McManus 1993, Wheelock and Wilson 2001). More recent literature has refuted these findings, suggesting that even the four largest banks in the U.S. today exhibit economies of scale that increase with bank size (Hughes et al. 2001, Feng and Serletis 2010, Wheelock and Wilson 2012).

Entries, by comparison, have been at unprecedented lows in recent years, particularly since 2010. Prior to 2010, new entries averaged 1.5 percent of existing bank stock. In the years immediately after 2010, that figure fell to 0.05 percent (McCord and Prescott 2014). Only 12 new bank charters were granted between 2010 and 2017. 2011 was the first year on record in which no new bank charters were granted, a phenomenon which was repeated in 2012, 2014, and 2016. The number of applications for de novo charters dropped off significantly after 2010, a decline which was only exacerbated by a drop in the rate of FDIC approval for those applications. The FDIC does not publish statistics regarding the number of applications for deposit insurance that it receives, but the law firm Arnold & Porter reports that the agency received more than 1,600 de novo applications for deposit insurance from 2000 to 2007 and approved more than 75 percent of these (Vallabhaneni 2017). During the height of the financial crisis from 2008 to 2010, Arnold &

Porter reports that only 20 percent of applications were approved. 119 de novo charters were granted during this period, implying that approximately 600 applications were filed. Based on these numbers, the FDIC received on average approximately 200 new charter applications per year during the period from 2000-2010. This is dramatically higher than the number of applications filed in every year after 2010. Arnold & Porter reports that, from 2011 to July 2016, only total 10 applications were filed, three of which were approved (Vallabhaneni 2017).

Since most new banks are small when they enter the market, a disproportionate regulatory burden for small banks could explain the lack of new bank entry in the post-Dodd-Frank period. Adams and Gramlich (2016) examined the decline in new charter activity and found evidence to suggest that the phenomenon was largely due to economic, not regulatory, factors. Rather than regulation, Adams and Gramlich find that the rate of de novo entry closely tracks the federal funds rate, which reached historic lows in the wake of the 2008 financial crisis. New banks' incomes are more tied to this interest rate than are old banks' incomes, and the low net interest margin and decline in demand for banking services cut dramatically into the potential profits that a de novo bank could expect to earn (Adams and Gramlich 2016). As a result, Adams and Gramlich found that as much as 75 percent of the decline in de novo entry observed in 2010 would have occurred without any change in regulation. Indeed, as the federal funds rate has begun to increase from the record lows of the post-recession years, the number of de novo charters granted has also started to rise. As of January 2019, the target federal funds rate has risen to 2.5 percent from the prevailing post-recession low of 0.25 percent. Five new bank charters were approved in 2017, and six were approved in the first three quarters of 2018, the most recent data currently on record (FDIC 2018b).

2.2 Dodd-Frank Overview

President Obama signed the Dodd-Frank Wall Street Reform and Consumer Protection Act into law on July 21, 2010, in response to the financial crisis of 2007-2009. The introductory language of the Act states that its goal is “to promote the financial stability of the United States by improving accountability and transparency in the financial system, to end ‘too big to fail,’ to protect the American taxpayer by ending bail-outs, to protect consumers from abusive financial services practices, and for other purposes” (The Dodd Frank Wall Street Reform and Consumer Protection Act Enrolled Final Version – HR 4173).

Titles I and III of the Act reorganized the structure of the federal banking regulators in order to streamline and strengthen the regulatory process. Title I established the Financial Security Oversight Committee (FSOC) and the Office of Financial Research (OFR). Title III abolished the Office of Thrift Supervision, transferring its powers to the FDIC, Federal Reserve System, and the Office of the Comptroller of the Currency (OCC). Title III also permanently increased the amount of deposit insurance provided by the FDIC to $250,000 from $100,000.

Title II endowed the Federal Deposit Insurance Corporation with Orderly Liquidation Authority, which requires systemically important firms to maintain a living will that details how they will be liquidated in the case that they become insolvent. This authority is meant to prevent bailouts of firms that would otherwise pose a threat to the national economy if they were to fail. The FDIC serves as the receiver for any bank that executes its living will.

Section 619 of the Act, known as the Volcker Rule, amends the Bank Holding Company Act of 1956 to ban financial firms from engaging in proprietary trading and acquiring or retaining “any equity, partnership, or other ownership interest in or sponsor a hedge fund or a private equity fund.” Few community banks engage in such activities, and therefore banks with fewer than $10 billion in assets have been exempt from "compliance obligations under the Final Rule if they do not engage in any covered activities."

Title X authorized the creation of the Consumer Financial Protection Bureau (CFPB), which has supervisory authority over "very large banks, savings associations, and credit unions," defined as those institutions with assets in excess of $10 billion. Banks smaller than $10 billion are exempt from examinations and regulation by the Bureau. The CFPB has the authority to "require reports and conduct examinations on a periodic basis" in order to assess compliance with Federal consumer financial laws, obtain "information about the activities subject to such laws and the associated compliance systems or procedures," and detect and assess "associated risks to consumers and to markets."

Other provisions of the Act include a requirement that the SEC regulate "over the counter" derivatives trading and that all hedge funds register with the SEC.

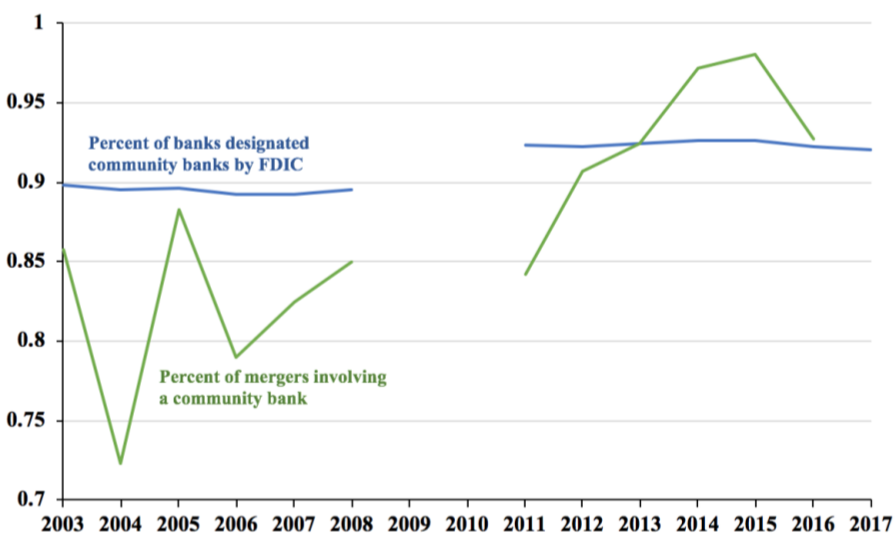
In May of 2018, Congress passed the Economic Growth, Regulatory Relief and Consumer Protection Act, which weakened significant pieces of the Dodd-Frank Act.

2.3 Impact of Regulation on Small Banks

Critics of Dodd-Frank argue that the greatest harm done by the law is to small and community banks, as they are less able than large banks to withstand the additional regulatory costs it imposes, and thus the law likely drives merger activity. A 2014 survey of small banks by the Mercatus Center reported that 90 percent of survey respondents saw increased compliance costs, the median respondent had increased their compliance staff from one to two employees, and more than 25 percent of respondents anticipated further hiring to deal with compliance. This finding is particularly significant given the finding from Feldman et al. (2013) that hiring two more compliance staff would make a third of small banks unprofitable. The survey from the Mercatus

Center also found that small banks were cutting or planned to cut the range of products they offered as a result of Dodd-Frank, that they felt that their ability to assess creditworthiness based on relationships (a historical advantage of community banks) was diminished as a result of Dodd-Frank, and that more than a quarter of small banks anticipated taking part in a merger or acquisition "in the near future." Lux and Greene (2015) expressed the view that the law creates "an uneven regulatory playing field that is accelerating consolidation for the wrong reasons." Figure 4.1 shows how the proportion of mergers that result in the exit of a community bank from the market has increased relative to the share of community banks during the post-Dodd-Frank period. For the period from 2013 to 2016, the share of mergers that involved a community bank actually exceeded the share of banks that were considered community banks for the first time since 2002. Data on which banks met the FDIC's definition of "community banks," which this paper utilizes, are only available from 2002 onward, so it is unclear how the trends of the last 17 years compare to previous decades. Still, the relative increase in the proportion of mergers that involve community banks in the post-Dodd-Frank period is noticeable.

Figure 4.1: Community Bank Mergers vs. Community Banks



Kowalik et al. (2015) found that post-Dodd-Frank mergers of small banks (with fewer than $1 billion in assets) typically led to greater economies of scale and efficiency. Banks merge to achieve these economies of scale, increase their revenue, reduce risk, or expand their footprint (DeYoung 2009, Hannan and Piloff 2009, Jagtiani 2008, Wheelock and Wilson 2000). Kowalik et al. measure community banks' median asset size, return on average assets (as measured by net interest income, non-interest income, and non-interest expenses), efficiency ratio (non-interest expenses divided by the sum of net interest income and non-interest income), capital holdings, and asset portfolio quality. They find that banks that are acquired in mergers tend to be "smaller, less profitable, less efficient, and in weaker condition than their non-acquired peers." They also tend to have lower CAMELS ratings than banks that remain in the market (Kowalik et al. 2015). Bank supervisors assess banks using the CAMELS rating system, which uses six criteria:

1. Capital adequacy
2. Asset quality
3. Management
4. Earnings
5. Liquidity
6. Sensitivity to market risk

The bank examiner scores each of the six subcategories on a one to five scale, with one being "strong" and five being "critically deficient." The six subscores are then compiled to determine a bank's overall CAMELS rating. Rather than weighting the components equally, the examiner determines how each category will be weighted based on their own risk assessment. Any bank that scores a three, four, or five overall will typically have to enter into an agreement with bank supervisors in order to resolve its issues (Lopez 1999, Stackhouse 2018). Neither a bank's CAMELS score nor the exact formula for its calculation are ever released to the public, so it is Kowalik et al.'s affiliation with the Federal Reserve that allows them to include it in their analysis.

The findings of Kowalik and his coauthors imply that, under the right conditions, mergers and acquisitions are an overall positive force, making the banking industry stronger and more efficient.

A significant body of research addresses the characteristics of banks that fail. This literature on what makes a bank stronger or weaker can be useful in determining the relative strength or weakness of banks that merged or were acquired before and after the passage of Dodd-Frank. Predictably, a bank's CAMELS score is highly correlated with probability of failure, as are the individual components that determine a bank's CAMELS score, namely capital levels, asset quality, earnings levels, and liquidity (Cole and White 2012). Cole and White (2012) examined bank failures during and immediately after the 2009 financial crisis and found that CAMELS scores were just as accurate at predicting failure during that crisis as they were during the banking crisis that occurred from 1985-1992, implying that the predictors of failure remain relatively constant across time periods.

Lu and Whidbee (2016) examined the characteristics of banks that received regulatory intervention during the 2009 financial crisis in order to understand differences between banks that failed and banks that were bailed out by the federal government. Variables associated with both failure and bailout indicate weaknesses within a bank, but regulators' decisions of which banks to bail out and which to allow to fail during the crisis can offer some insight as to which variables matter most when determining when a bank is too weak to remain in the market. Lu and Whidbee found that a larger proportion of non-performing loans made a bank more likely to fail and less likely to receive Capital Purchase Program (CPP) funds from regulators. Other authors have historically found that poor asset quality, lending practices, and management, as well as abuse by bank insiders, are all correlated with bank failure, although these variables are not included in my dataset and therefore will not be included in my analysis (Office of the Comptroller of the Currency 1988, Cole and White 2012, DeYoung and Torna 2013).

2.4 Regulatory Thresholds

The authors of Dodd-Frank were aware of the threat of overburdening community banks and attempted to reduce that burden by implementing asset thresholds in the law below which banks would be subject to decreased regulatory scrutiny. Prior to the 2018 enactment of the Economic Growth, Regulatory Relief and Consumer Protection Act, which raised multiple thresholds enacted in the Dodd-Frank Act, banks with less than $10 billion in assets were exempted from some of the law's major requirements. Banks smaller than $10 billion are not required to administer or report results for annual company-run stress tests, nor are they subject to quarterly assessments or other regulatory oversight by the CFPB. Banks under $10 billion do not need to abide by restrictions on debit card interchange fees under Dodd-Frank's Durbin Amendment (Dodd-Frank Wall Street Reform and Consumer Protection Act 2010). These size-based exemptions create a regulatory threshold that is costly for banks to cross. The implementation of company-run stress tests and CFPB quarterly examinations in particular require significant additional compliance efforts from a bank. Nicoletti et al. (2017) found that the existence of this threshold increases demand for acquisitions by banks that are "approaching and just above" $10 billion in assets. The additional regulatory requirements for banks above this threshold are significant but do not vary greatly with size above $10 billion. These costs therefore become a smaller burden as banks continue to grow above the $10 billion threshold, creating an incentive for them to acquire other banks in order to grow more quickly and improve their return on assets. Nicoletti et al. hypothesize that banks that pass the $10 billion threshold must grow to at least $12 billion in assets in order to fully offset the costs of regulation on financial statement ratios. They compare the acquisition activity of banks with between $9 and 12 billion in assets to banks with between $5 and 9 billion and between $12 and 16 billion, and they find that banks near the threshold are more likely to pay a premium for acquisition targets or acquire banks that would not previously have been targets. Their conclusion is that the regulatory thresholds present in the Dodd-Frank Act created demand for acquisitions which would otherwise not have occurred.

Numerous authors, including Nicoletti et al., find that regulatory thresholds have distortionary effects on the behavior of firms with assets or sales below the threshold, creating disincentives for firms to grow above a certain size and leading to "bunching" of firms at a size that leaves them just below the threshold. Much of the research on this phenomenon studies industries outside of the banking sector. St. Clair (2016) examined two such thresholds in New York State that imposed additional reporting requirements on charitable organizations with annual revenue above $100,000 and $250,000, above which organizations are required to "file financial statements reviewed by or audited by an independent certified public accountant," respectively. Compared to a counterfactual regression, charities near the lower threshold reported nearly $1,300 less than predicted, and charities near the higher regression reported nearly $1,400 less (St. Clair 2016). Similarly, analysis of Section 404(b) of the 2002 Sarbanes-Oxley legislation, which requires the auditors of companies with more than $75 million in publicly-held shares (also known as public float) to attest to management's assessment of its internal controls, found evidence that firms around the threshold reduced their public float by an average of $1.7 million, leading to significant bunching below the threshold (Dharmapala 2016). Onji (2009) found that, in order to artificially keep sales below a certain level to avoid losing tax benefits, large firms in Japan would go so far as to reconfigure their organizational structures to incorporate segments of the company as legally separate entities with sales below the eligibility threshold. This phenomenon, which Onji refers to as "tax-motivated splitting," resulted in significant bunching of firms with sales just below 500 million yen. All of these analyses suggest that firms will change their behavior and even forego revenue-raising activity when they are near regulatory thresholds in order to avoid incurring additional regulatory burden.

3. Data

This paper uses quarterly balance sheet and qualitative information on FDIC-insured banking institutions from the FDIC Community Banking Study Reference Data. The samples used in this study include every bank-quarter observation from 2003 to 2008 and 2011 to 2017. I chose to omit data from 2009 and 2010, as those are the years during which Dodd-Frank was under discussion in the legislature, and those years are also most subject to the forces of the Great Recession and therefore may not be representative of overall trends (Nicoletti et al. 2017).

I obtained information on exit activity during the observation period from the FDIC's Community Banking Structure Reference Data, which documents every entry and exit of a banking institution from the universe of FDIC insurance. Mergers between banks that were already under common ownership four quarters prior to the observation are omitted. During the relevant quarters, we observe 235 failures, 55 of which occurred in the pre-period and 180 of which occurred in the post-period, and 2,557 mergers and acquisitions, 1,246 of which occurred in the pre-period and 1,311 of which occurred in the post-period.

I also use data from FRED, the economic database of the Federal Reserve Bank of St. Louis, to document the effective federal funds rate for each quarter in the observation period.

My final dataset merges the three sources mentioned above to offer a full picture of exits from 2003-2008 and 2011-2017. In total, this dataset includes 397,379 bank-quarter observations. Each bank-quarter observation details information about bank *i* in quarter *t*. A binary variable "*mna*" equals 1 if bank *i* exited the market through merger or acquisition in quarter $t + 1$. Similarly, a binary variable "*failure*" equals 1 if bank *i* failed in quarter $t + 1$. For example, for a bank that was acquired in Q3-2008, *mna* will equal 0 in Q4-2007, 0 in Q1-2008, and 1 in Q2-2008, signifying that the bank was acquired in the quarter immediately following the Q2-2008 observation. There would be no observation for that bank in Q3-2008. This is due to the fact that bank-quarter data is generated on the final day of the quarter; therefore the final observation of a merging bank is from the quarter immediately prior to the merger.

4. Descriptive Analysis of the Characteristics of Merged and Acquired Banks

4.1 Model

I use a logit regression that models the characteristics of banks that exited the market through failure, merger, or acquisition in the pre- and post-periods in order to understand changes in the nature of consolidation activity before and after the passage of Dodd-Frank. The outcome in this case is a discrete variable; either bank *i* exits the market in quarter $t + 1$, in which case the dependent variable is equal to 1, or it does not, and the dependent variable is equal to 0. I model the exit outcome as a function of both quantitative balance sheet variables and qualitative information about a bank. I include the effective federal funds rate to account for the impact of the macroeconomy on merger and acquisition activity, since mergers and acquisitions are more likely in strong economies and less likely in weak ones (Jacobs 2018). I include an interaction term that describes whether a bank is considered a "community bank" by the FDIC's research definition in order to examine any changes in merger and acquisition activity that specifically apply to community banks. I use interaction terms to show changes from the pre-period to the post-period.

Summary of FDIC Research Definition of Community Banking Organizations

Designate community banks at the level of the banking organization. All charters under designated holding companies are considered community banking charters.

Exclude:

Any organization with:
- No loans or no core deposits
- Foreign Assets ≥ 10% of total assets
- More than 50% of assets in certain specialty banks, including:
  - credit card specialists
  - consumer nonbank banks[1]
  - industrial loan companies
  - trust companies
  - bankers' banks

[1] Consumer nonbank banks are financial institutions with limited charters that can make commercial loans or take deposits, but not both.

Include:

All remaining banking organizations with:
- Total assets < indexed size threshold[2]
- Total assets ≥ indexed size threshold, where:
  - Loan to assets > 33%
  - Core deposits to assets > 50%
  - More than 1 office but no more than the indexed maximum number of offices.[3]
  - Number of large MSAs with offices ≤ 2
  - Number of states with offices ≤ 3
  - No single office with deposits > indexed maximum branch deposit size.[4]

[2] Asset size threshold indexed to equal $250 million in 1985 and $1 billion in 2010.
[3] Maximum number of offices indexed to equal 40 in 1985 and 75 in 2010.
[4] Maximum branch deposit size indexed to equal $1.25 billion in 1985 and $5 billion in 2010.

Source: FDIC.

The bank characteristics I include in my model include the natural log of a bank's assets (*logAssets*), its ratio of liabilities to assets (*LOA*), its ratio of intangible assets to tangible assets (*IntanIntensity*), its gross loan and lease financing receivable charge-offs less gross recoveries (annualized) as a percent of average total loans and lease financing receivables (*ntlnlsr*), its ratio of net operating income to assets (*noijy*), its yield on earning assets (*intincy*), and whether it is in an urban location (*inMSA*). The balance sheet variables I select are based largely on those that previous researchers have found to be important and upon the statistics that bank examiners use to calculate a firm's CAMELS rating. I include a variable to denote whether a bank is headquartered in an urban location because this distinction captures many factors about the competitive environment in which a bank operates. Median incomes are higher in urban areas, as are poverty and income inequality (Bishaw and Posey 2016). Urban banking markets are also typically much less concentrated than rural markets, leading to both increased competition and greater potential for mergers. Regulators calculate the concentration of a banking market using the Herfindahl-Hirschman Index of deposit shares in the area, but this is difficult to accomplish for every bank in the country, so whether or not a bank is headquartered in an urban location can help give an idea of the competitive environment in which it operates (Meyer 2018).

A shortened form of the model is as follows:

$$
\begin{aligned}
&\mathit{Probability(Merger\ or\ Acquisition)}_{i,t+1} = \beta_0 + \beta_1(\mathit{Federal\ Funds\ Rate})_t \\
&\quad + \beta_2(\mathit{Bank\ Characteristics})_{i,t} + \beta_3(\mathit{Bank\ Characteristics{*}cb})_{i,t} \\
&\quad + \beta_4(\mathit{Bank\ Characteristics{*}post})_{i,t} + \beta_5(\mathit{Bank\ Characteristics{*}cb{*}post})_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

The complete version of the model is:

$$
\begin{aligned}
&\mathit{Probability(Merger\ or\ Acquisition)}_{i,t+1} = \beta_0 + \beta_1(\mathit{Federal\ Funds\ Rate})_t + \beta_2(\mathit{logAssets}) \\
&\quad + \beta_3(\mathit{LOA}) + \beta_4(\mathit{IntanIntensity}) + \beta_5(\mathit{ntlnlsr}) + \beta_6(\mathit{noijy}) + \beta_7(\mathit{intincy}) \\
&\quad + \beta_8(\mathit{inMSA}) + \beta_9(\mathit{logAssets{*}post}) + \beta_{10}(\mathit{LOA{*}post}) + \beta_{11}(\mathit{IntanIntensity{*}post}) \\
&\quad + \beta_{12}(\mathit{ntlnlsr{*}post}) + \beta_{13}(\mathit{noijy{*}post}) + \beta_{14}(\mathit{intincy{*}post}) + \beta_{15}(\mathit{inMSA{*}post}) \\
&\quad + \beta_{16}(\mathit{logAssets{*}cb}) + \beta_{17}(\mathit{LOA{*}cb}) + \beta_{18}(\mathit{IntanIntensity{*}cb}) + \beta_{19}(\mathit{ntlnlsr{*}cb}) \\
&\quad + \beta_{20}(\mathit{noijy{*}cb}) + \beta_{21}(\mathit{intincy{*}cb}) + \beta_{22}(\mathit{inMSA{*}cb}) + \beta_{23}(\mathit{logAssets{*}post{*}cb}) \\
&\quad + \beta_{24}(\mathit{LOA{*}post{*}cb}) + \beta_{25}(\mathit{IntanIntensity{*}post{*}cb}) + \beta_{26}(\mathit{ntlnlsr{*}post{*}cb}) \\
&\quad + \beta_{27}(\mathit{noijy{*}post{*}cb}) + \beta_{28}(\mathit{intincy{*}post{*}cb}) + \beta_{29}(\mathit{inMSA{*}post{*}cb}) + \varepsilon_{i,t}
\end{aligned}
$$

4.2 Results: Mergers and Acquisitions

In order to fully understand the impact of these probabilities, I determined the predicted probability of exiting the market through merger or acquisition for community and non-community banks in both the pre- and post-Dodd-Frank periods, holding all of the balance sheet variables listed here at their means. To avoid biasing these results with the impact of macroeconomic variables on the likelihood of merger and acquisition activity, I normalize the federal funds rate for the pre- and post-periods. These results are reported in Table 1. The absolute likelihood of engaging in a merger or acquisition are low for both types of banks in both time periods and fell significantly after the passage of Dodd-Frank. The decline in merger and acquisition activity is slightly less pronounced for community banks. This observation is not meant to carry the weight of a differences-in-differences analysis, as non-community banks cannot serve as a real control group for community banks, but it may offer some descriptive insight into the dynamics of merger and acquisition activity post-crisis.

Table 1: Odds of Exiting Market through Merger or Acquisition In A Given Quarter

	Pre-Dodd-Frank	Post-Dodd-Frank	Change
Community Banks	0.548%	0.391%	−28.5%
Non-Community Banks	1.134%	0.760%	−32.9%

The full results of the model are displayed in Table 2. Given the large number of observations in my data, I use a 99 percent threshold for statistical significance in my analysis.

Table 2: Merger and Acquisition Results

Variable	Coefficient	Probability
Effective Federal Funds Rate	0.175*** (0.018)	**54%**
log(Assets)	-0.066* (0.038)	48%
Liabilities to Assets	0.051*** (0.014)	**51%**
Intangible Assets to Assets	0.110*** (0.014)	**53%**
Net Charge-offs to Loans	-0.014*** (0.004)	**50%**
Net Operating Income to Assets	0.045*** (0.017)	**51%**
Yield on Earning Assets	-0.432*** (0.039)	**39%**
Urban Location	-0.234 (0.198)	44%
Post-Dodd-Frank ("Post")	2.624* (1.507)	93%
Community Bank ("CB")	-5.695*** (1.336)	**0%**
log(Assets) * CB	0.013 (0.049)	50%
Liabilities to Assets * CB	0.042*** (0.015)	**51%**
Intangible Assets to Assets * CB	0.069*** (0.018)	**52%**
Net Charge-offs to Loans * CB	-0.023 (0.020)	49%
Net Operating Income to Assets * CB	-0.161*** (0.020)	**46%**
Yield on Earning Assets * CB	0.130*** (0.048)	**53%**
Urban Location * CB	0.872*** (0.211)	**71%**
Post * CB	4.328** (1.848)	99%
log(Assets) * Post	-0.149* (0.065)	46%
Liabilities to Assets * Post	-0.029 (0.016)	49%
Intangible Assets to Assets * Post	-0.018 (0.024)	50%
Net Charge-offs to Loans * Post	-0.024 (0.073)	49%
Net Operating Income to Assets * Post	-0.060*** (0.022)	**49%**
Yield on Earning Assets * Post	0.226*** (0.081)	**56%**
Urban Location * Post	1.163*** (0.408)	**76%**
log(Assets) * Post * CB	0.050 (0.077)	51%
Liabilities to Assets * Post * CB	-0.026 (0.020)	49%
Intangible Assets to Assets * Post * CB	-0.043 (0.035)	49%
Net Charge-offs to Loans * Post * CB	-0.034 (0.081)	49%
Net Operating Income to Assets * Post * CB	-0.016 (0.030)	50%
Yield on Earning Assets * Post * CB	-0.341*** (0.092)	**42%**
Urban Location * Post * CB	-1.180*** (0.419)	**23%**
Constant	-6.315*** (1.086)	**0%**

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

Prior to the passage of Dodd-Frank and the financial crisis, a bank's liabilities, intangible assets, and net operating income were all positively correlated with the likelihood of merging or being acquired. A 100 basis point increase in a bank's ratio of liabilities to assets was associated with a 51 percent increase in the probability that that bank will merge. A 100 basis point increase in a bank's ratio of intangible assets to assets was associated with a 53 percent increase in the probability that that bank would merge. A 100 basis point increase in net operating income to assets was associated with a 51 percent increase in the likelihood that a bank would merge. Non-performing loans and yield on earning assets were both negatively correlated with merger and acquisition activity. Banks that merged or were acquired had a lower net charge-off rate, but also saw lower yield on their earning assets. A 100 basis point decrease in net charge-offs to loans was associated with a 50 percent increase in the probability that a bank would merge, and a 100 basis point decrease in a bank's yield on earning assets was associated with a 39 percent increase in the likelihood that a bank would merge.

For community banks in particular in the pre-Dodd-Frank era, liabilities and intangible assets were even more positively associated with the likelihood of merging or being acquired. The trends in net operating income to assets and yield on earning assets for merged or acquired non-community banks were attenuated for community banks. Merged community banks had lower net operating income to assets but higher yield on earning assets than merged non-community banks in the pre-Dodd-Frank period, suggesting that they did a better job than their non-community bank peers of managing assets, but had lower profit margins. Community banks that merged in the pre-Dodd-Frank era were also much more likely than the average bank to be urban, with an urban headquarters being associated with a 71 percent increase in the likelihood of merger.

After the passage of Dodd-Frank, urban banks became somewhat more likely to merge. Being headquartered in an urban location was associated with a 76 percent increase in the probability that a bank would merge in the post-period. Merged banks were also less profitable, with lower net operating incomes than banks that merged in the pre-period, but those banks also had higher yield on earning assets than in the pre-period. Merged community banks in the post-period were less likely to be urban and had lower yield on earning assets relative to other banks than in the pre-Dodd-Frank period, but showed no other significant deviations from pre-Dodd-Frank or non-community bank trends. The latter variable offers some suggestion that the financial strength of merged and acquired community banks declined relative to other banks in the post-Dodd-Frank period.

As expected given the positive correlation between a strong economy and merger rates, the effective federal funds rate is a significant and positive predictor of mergers and acquisitions. Every rate increase of 100 basis points is correlated with a 54 percent increase in the probability of a merger or acquisition.

4.3 Results: Failures

In order to determine which of the variables described above are correlated with bank failure, I run an abridged form of my exit regression:

$$Probability(Failure)_{i,t+1} = \beta_0 + \beta_1(Federal\ Funds\ Rate)_t + \beta_2(logAssets) + \beta_3(LOA) + \beta_4(IntanIntensity) + \beta_5(ntlnlsr) + \beta_6(noijy) + \beta_7(intincy) + \beta_8(inMSA) + \varepsilon_{i,t}$$

Results of this regression are reported in Table 3.

Table 3: Failure Results

Variable	Coefficient	Probability
Effective Federal Funds Rate	-0.318***	**42%**
	(0.090)	
log(Assets)	0.092	52%
	(0.065)	
Liabilities to Assets	0.965***	**72%**
	(0.034)	
Intangible Assets to Assets	0.303***	**58%**
	(0.136)	
Net Charge-offs to Loans	0.017	50%
	(0.020)	
Net Operating Income to Assets	-0.093***	**48%**
	(0.028)	
Yield on Earning Assets	0.186**	55%
	(0.065)	
Urban Location	0.236	56%
	(0.209)	
Constant	-99.194***	
	(3.458)	

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

Because the definition of when a bank has failed remains essentially constant, I do not include interaction terms for either time period or community bank status in this regression (Cole and White 2012).[3] These results, in addition to the findings of previous authors outlined in my literature review, help create a baseline for what characteristics define a weak or failing bank, which I can then use to approximate the relative strength or weakness of banks that exit the market through merger and acquisition during the pre- and post-periods.

[3] Failure regressions that include both time period and community bank interaction terms can be found in Appendix C.

I find that failed banks tend to have more liabilities and intangible assets as a portion of assets than the average bank, findings which are also true of merged or acquired banks in both periods. There was no statistically significant change in either of these trends from the pre-Dodd-Frank to post-Dodd-Frank periods. Failed banks are also less profitable than non-failed banks, having lower net operating incomes than non-failed banks. Merged banks in the post-period saw a significant decline in their net operating incomes as compared to pre-period trends, suggesting that banks that merged in the post-Dodd-Frank period were weaker on at least one significant level. The sign on yield on earning assets for failed banks is not intuitive, but statistically less significant than other variables. Some of the other major predictors of failure, including poor management and fraud, are not included in this dataset. These results, then, only address similarities in the balance sheets of banks that merged or were acquired and banks that failed.

5. Impact on Merger and Acquisition Activity of Banks with $5.5–8.5 Billion in Assets

I use a differences-in-differences model to test the hypothesis that banks with between $5.5 and 8.5 billion in assets decreased their merger and acquisition activity in response to regulatory thresholds present in the Dodd-Frank Act. This model compares changes in the merger and acquisition activity of banks in my treatment group from the pre- to the post-Dodd-Frank periods to changes in the merger and acquisition activity of banks in two different control groups. The first such control group is banks with between $3.5 and 5.5 billion in assets; the second is banks with between $8.5 and 12 billion in assets. I use both larger and smaller banks as controls to mitigate any fundamental differences in merger and acquisition behavior between the treatment group and banks that are exclusively smaller or exclusively larger. A bank is assigned to the treatment or control groups based on its asset levels in the first quarter of 2011, which is the first quarter after the passage of Dodd-Frank that is included in my dataset. If a bank had between $5.5 and 8.5

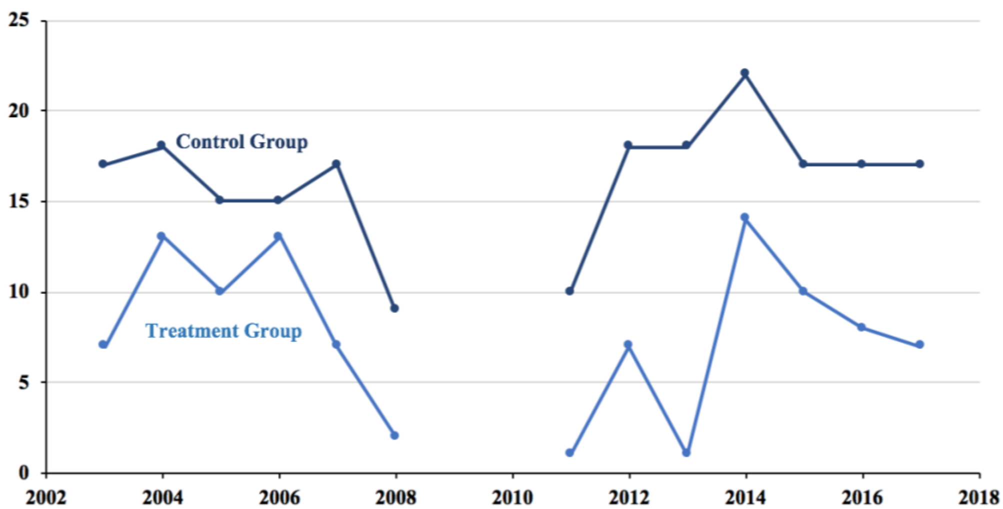
billion in assets in that quarter, it is assigned to the treatment group; if it had between $3 and 5.5 billion or $8.5 and 12 billion in assets, it is assigned to the control, and this assignment does not change. This way, I am able to avoid the possibility that banks' natural asset growth might cause individual institutions to move between the control and treatment groups over the time period in question. I also remove any banks that merged or failed out of existence from my treatment and control groups in order to maintain the Stable Unit Treatment Value Assumption.

I chose my treatment group for the following reasons: In the period in question, the average rate of asset growth for banks in the treatment group was 1.89 percent per quarter. At such a rate, these banks would not naturally grow above the $10 billion threshold for a matter of years. $8.5 billion banks would surpass the threshold after about 10 quarters; $5.5 billion banks would surpass it after about 33 quarters. $9 billion banks, by comparison, grew at an average rate of about 2.21 percent, and thus would expect to naturally surpass the $10 billion threshold after only about a year. When banks in the treatment group merge, the mean asset size of banks they merge with is about $531 million, and the median is about $349 million. For many treatment banks, then, engaging in a merger or acquisition would increase their asset base to a degree that they could expect to quickly surpass the $10 billion threshold.

There are 5,772 bank-quarter observations in this dataset. Of those, 1,248, or 21.6 percent, are treatment observations. 88.4 percent are control observations, of which 56.8 percent of the total control observations are from the smaller group and 21.6 percent are from the larger group. A merger or acquisition occurs in approximately 5.4 percent of the bank-quarter observations in the sample. Note that in contrast to the previous section, which examined the characteristics of banks that exited the market through merger or acquisition, this section looks at the merger and acquisition activity of banks that remained in the market after the activity in question.

To provide support for the parallel trends assumption, Figure 6.1 shows the number of mergers and acquisitions made by treatment and control groups in the pre- and post-Dodd-Frank periods. The two groups share essentially the same trends in merger and acquisition activity in the pre-Dodd-Frank period, going through the same upturns and downturns year-over-year, which lends support to the idea that the parallel trends assumption holds in this case.

Figure 6.1: Mergers and Acquisitions by Year



I test my hypothesis with the following logistic regression, which utilizes the same control variables as the descriptive regressions found in Section 5:

$$Probability(Acquisition)_{i,t+1} = \beta_0 + \beta_1 {*} treat_t + \beta_2 {*} post_i + \beta_3 {*} treat {*} post_{i,t} + \beta_4 {*} logAssets_{i,t} + \beta_5 {*} LOA_{i,t} + \beta_6 {*} IntanIntensity_{i,t} + \beta_7 {*} ntlnlsr_{i,t} + \beta_8 {*} noijy_{i,t} + \beta_8 {*} intincy_{i,t} + \varepsilon_{i,t}$$

The results of this regression are reported in Table 4. The differences in the differences in merger and acquisition activity between banks in the treatment and control groups from the pre- to the post-Dodd-Frank periods are both economically and statistically significant. I find that in the pre-Dodd-Frank period, banks in the treatment group were 51.0 percent more likely to merge with or acquire another bank than were banks in the control groups. In the post-Dodd-Frank period, however, that difference is mitigated. Banks in the treatment group significantly decreased their merger and acquisition activity in the wake of Dodd-Frank, becoming 48.9 percent less likely to acquire or merge with another bank than in the pre-Dodd-Frank period relative to the control group.

Table 4: Differences-In-Differences Results

Variable	Coefficient	Probability
Treat	0.039*** (0.011)	**51.0%**
Post	0.014 (0.009)	50.3%
Treat*Post	-0.043*** (0.015)	**48.9%**
log(Assets)	0.001 (0.005)	50.0%
Liabilities to Assets	0.002** (0.001)	**50.1%**
Intangible Assets to Assets	0.011*** (0.002)	**50.3%**
Net Charge-offs to Loans	-0.013*** (0.004)	**49.7%**
Net Operating Income to Assets	0.004* (0.002)	50.1%
Yield on Earning Assets	0.003 (0.002)	50.1%
Urban Location	-0.042*** (0.009)	**49.0%**
Constant	-0.160 (0.111)	

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

Due to the relatively small number of actual mergers and acquisitions that occur during this period, the results I offer above are suggestive of the asset thresholds' impact on the treatment group rather than definitive. Additional analyses that could support the conclusion that regulatory asset thresholds diminished merger and acquisition activity, such as an analysis of deal premiums paid by banks during the time period such as the one conducted by Nicoletti et al., would require data beyond what I have been able to obtain here. Still, the results of the test above are significant at the 99 percent level, suggesting that a real change in behavior likely occurred. Additionally, the finding that these firms decreased their merger and acquisition activity in response to regulatory thresholds aligns with the results of Onji 2009, Dharmapala 2016, and St. Clair 2016, all of which find that firms will substantially alter their behavior in order to avoid additional regulatory burden.

6. Conclusion

Overall, my results do not suggest that the Dodd-Frank Act has contributed to a harmful increase in consolidation activity in the U.S. banking industry, as some of its critics have suggested. On a purely descriptive level, I find relatively few changes in the predictors of merger and acquisition activity among banks when comparing the pre- and post-Dodd-Frank periods, and even fewer that affect community banks in particular. The only variables for which there was a statistically significant change in trend in the post-Dodd-Frank period are urban location, net operating income, and yield on earning assets. I find that urban banks have become more likely to merge, but this effect is mitigated among community banks. In the post-Dodd-Frank period, merged banks are less profitable relative to their peers than they were in the pre-Dodd-Frank period, and merged community banks in particular have lower yield on earning assets. My findings suggest that if anything has changed about the nature of consolidation in the time since Dodd-Frank was passed, it is not affecting community banks with strong balance sheets, but is affecting those with relatively weak ones. The banks that are statistically significantly more likely to merge in the post-Dodd-Frank period are also the banks that are most comparable to their failed peers.

Additionally, my results suggest that regulatory thresholds present in the Act may have actually suppressed some merger and acquisition activity among banks that had between $5.5 and 8.5 billion in assets in the period just after the Act was passed. Provisions in the Dodd-Frank Act which exempted banks with less than $10 billion in assets from regulation by the Consumer Financial Protection Bureau (CFPB), annual company-run stress tests, and the Durbin Amendment may have actually created incentives for banks whose natural rate of asset growth would not otherwise bring them above the $10 billion threshold to forego merger and acquisition activity in order to avoid becoming subject to additional regulatory scrutiny. It is important to note that since the Economic Growth, Regulatory Relief and Consumer Protection Act increased the threshold at which companies are required to carry out company-run stress tests in May of 2018, the impacts of this last finding are likely very different for all years after 2017, the last year in my sample.

Nevertheless, these findings suggest that during the period from 2011 to 2017, before the Dodd-Frank Act was amended, the law was not the driver of consolidation that critics made it out to be. The consolidation of the banking industry that began in 1985 has continued in the post-Dodd-Frank era, but the fundamental balance sheet characteristics of the banks that are merging or being acquired do not indicate that the healthiest banks are being driven out of the market, nor are healthy community banks at particular risk. Nor is consolidation necessarily on the rise in all segments of the banking industry. My analysis suggests that banks that had between $5.5 and 8.5 billion in assets in the period just after the passage of Dodd-Frank actually decreased their merger and acquisition activity in that period, a finding which is in line with prior authors' analyses of the impact of regulatory thresholds in other industries. Overall, I find evidence that the impacts of the Dodd-Frank Wall Street Reform and Consumer Protection Act on consolidation trends in the United States banking industry were minimal and do not offer cause for concern.

Appendix A. Distribution of Variables

Table 5: Distributional Statistics

Variable	N	Mean	Std Dev	10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl
Federal Funds Rate	397379	0.017	1.81	0.009	0.14	1.00	2.94	5.07
Assets (in 1,000s)	397379	1758649	32001877	35619	68293	144148	337991	873108
Liabilities to Assets	397379	88.17%	7.75%	83.99%	87.50%	89.72%	91.22%	92.28%
Intangible Assets to Assets	397379	0.52%	2.07%	0.00%	0.00%	0.00%	0.25%	1.40%
Net Charge-Offs to Loans	397379	0.28%	2.36%	-0.0328%	0.00	0.06	0.26	0.72
Net Operating Income to Assets	397379	0.88%	3.37%	0.05%	0.49%	0.88%	1.29%	1.77%
Yield on Earning Assets	397379	5.35%	1.67%	3.62%	4.27%	5.27%	6.30%	7.13%

Appendix B. Correlation Matrix

	ffr	*logasset*	*liaboverasset100*	*rbc1aaj*	*intanratio100*	*ntlnlsr*	*noijy*	*intincy*	*inMSA*	*post*	*cb*
ffr		-0.087^{***}	-0.043^{***}	0.039^{***}	0.041^{***}	-0.030^{***}	0.013^{***}	0.551^{***}	0.017^{***}	-0.729^{***}	-0.037^{***}
logasset	-0.087^{***}		0.156^{***}	-0.113^{***}	0.210^{***}	0.033^{***}	0.061^{***}	-0.068^{***}	0.295^{***}	0.147^{***}	-0.470^{***}
liaboverasset100	-0.043^{***}	0.156^{***}		-0.569^{***}	-0.220^{***}	-0.018^{***}	0.028^{***}	0.084^{***}	-0.042^{***}	0.013^{***}	0.083^{***}
rbc1aaj	0.039^{***}	-0.113^{***}	-0.569^{***}		0.010^{***}	0.004^{*}	-0.056^{***}	-0.068^{***}	0.026^{***}	-0.023^{***}	-0.014^{***}
intanratio100	0.041^{***}	0.210^{***}	-0.220^{***}	0.010^{***}		0.011^{***}	0.056^{***}	0.000	0.061^{***}	-0.033^{***}	-0.256^{***}
ntlnlsr	-0.030^{***}	0.033^{***}	-0.018^{***}	0.004^{*}	0.011^{***}		-0.032^{***}	0.059^{***}	0.021^{***}	0.022^{***}	-0.047^{***}
noijy	0.013^{***}	0.061^{***}	0.028^{***}	-0.056^{***}	0.056^{***}	-0.032^{***}		0.105^{***}	-0.052^{***}	-0.007^{***}	-0.030^{***}
intincy	0.551^{***}	-0.068^{***}	0.084^{***}	-0.068^{***}	0.000	0.059^{***}	0.105^{***}		0.010^{***}	-0.592^{***}	-0.060^{***}
inMSA	0.017^{***}	0.295^{***}	-0.042^{***}	0.026^{***}	0.061^{***}	0.021^{***}	-0.052^{***}	0.010^{***}		-0.021^{***}	-0.182^{***}
post	-0.729^{***}	0.147^{***}	0.013^{***}	-0.023^{***}	-0.033^{***}	0.022^{***}	-0.007^{***}	-0.592^{***}	-0.021^{***}		0.047^{***}
cb	-0.037^{***}	-0.470^{***}	0.083^{***}	-0.014^{***}	-0.256^{***}	-0.047^{***}	-0.030^{***}	-0.060^{***}	-0.182^{***}	0.047^{***}	

Computed correlation used pearson-method with listwise-deletion.

Appendix C. Failure Regressions with Community Bank and Time Period Interaction Terms

Table 7: Failure Results with Time Period Interaction Terms

Variable	Coefficient	Probability
Effective Federal Funds Rate	-0.454*** (0.116)	**39%**
log(Assets)	0.163* (0.095)	54%
Liabilities to Assets	0.756*** (0.060)	**68%**
Intangible Assets to Assets	0.236 (0.156)	56%
Net Charge-offs to Loans	0.004 (0.042)	50%
Net Operating Income to Assets	-0.142*** (0.045)	**46%**
Yield on Earning Assets	0.212*** (0.042)	**55%**
Urban Location	0.471 (0.407)	62%
Post-Dodd-Frank ("Post")	-30.853*** (7.865)	**0%**
log(Assets) * Post	-0.173 (0.132)	46%
Liabilities to Assets * Post	0.356*** (0.081)	**59%**
Intangible Assets to Assets * Post	0.160 (0.332)	54%
Net Charge-offs to Loans * Post	0.024 (0.049)	51%
Net Operating Income to Assets * Post	0.087 (0.059)	52%
Yield on Earning Assets * Post	-0.238* (0.135)	44%
Urban Location * Post	-0.383 (0.478)	41%
Constant	-80.418*** (5.710)	

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

Table 8: Failure Results with Community Bank Interaction Terms

Variable	Coefficient	Probability
Effective Federal Funds Rate	-0.302*** (0.092)	**43%**
log(Assets)	0.090 (0.125)	52%
Liabilities to Assets	0.472*** (0.064)	**62%**
Intangible Assets to Assets	-0.162 (0.223)	46%
Net Charge-offs to Loans	0.009 (0.068)	50%
Net Operating Income to Assets	-0.152*** (0.033)	**46%**
Yield on Earning Assets	0.192*** (0.074)	**55%**
Urban Location	13.801 (377.927)	100%
Community Bank Status ("CB")	-40.759 (378.008)	0%
log(Assets) * CB	-0.020 (0.152)	50%
Liabilities to Assets * CB	0.575*** (0.074)	**64%**
Intangible Assets to Assets * CB	0.704*** (0.268)	**67%**
Net Charge-offs to Loans * CB	0.019 (0.070)	50%
Net Operating Income to Assets * CB	0.075* (0.045)	52%
Yield on Earning Assets * CB	-0.018 (0.111)	50%
Urban Location * CB	-13.569 (377.927)	0%
Constant	-66.015 (377.987)	

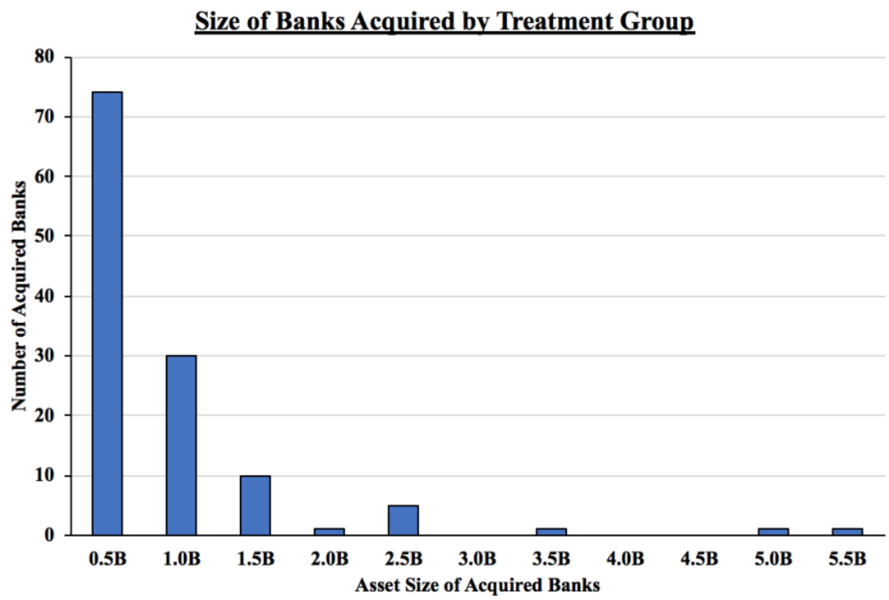
Note: $*$ $p<0.1$; $**$ $p<0.05$; $***$ $p<0.01$

Table 9: Failure Results with Time Period and Community Bank Interaction Terms

Variable	Coefficient	Probability
Effective Federal Funds Rate	-0.423*** (0.119)	**40%**
log(Assets)	0.197 (0.186)	55%
Liabilities to Assets	0.431*** (0.099)	**61%**
Intangible Assets to Assets	-0.065 (0.240)	48%
Net Charge-offs to Loans	0.033 (0.055)	51%
Net Operating Income to Assets	-0.158*** (0.032)	**46%**
Yield on Earning Assets	0.231*** (0.059)	**56%**
Urban Location	13.354 (513.962)	99%
Post-Dodd-Frank ("Post")	-29.411 (624.603)	0%
Community Bank Status ("CB")	-30.459 (514.084)	0%
log(Assets) * Post	-0.198 (0.284)	45%
Liabilities to Assets * Post	0.384* (0.215)	59%
Intangible Assets to Assets * Post	-0.359 (0.862)	51%
Net Charge-offs to Loans * Post	-0.124 (0.172)	47%
Net Operating Income to Assets * Post	0.346** (0.154)	59%
Yield on Earning Assets * Post	-0.519 (0.328)	37%
Urban Location * Post	-0.990 (624.250)	27%
log(Assets) * CB	0.081 (0.244)	52%
Liabilities to Assets * CB	0.461*** (0.117)	**61%**
Intangible Assets to Assets * CB	0.524* (0.295)	63%
Net Charge-offs to Loans * CB	0.017 (0.068)	50%
Net Operating Income to Assets * CB	0.092 (0.057)	52%
Yield on Earning Assets * CB	-0.092 (0.167)	48%
Urban Location * CB	-13.132 (513.962)	0%
Post * CB	3.852 (624.666)	98%
log(Assets) * Post * CB	-0.109 (0.341)	47%
Liabilities to Assets * Post * CB	-0.083 (0.232)	48%
Intangible Assets to Assets * Post * CB	0.435 (0.926)	61%
Net Charge-offs to Loans * Post * CB	0.104 (0.179)	53%
Net Operating Income to Assets * Post * CB	-0.354** (0.166)	41%
Yield on Earning Assets * Post * CB	0.490 (0.390)	62%
Urban Location * Post * CB	0.938 (624.250)	72%
Constant	-63.495 (514.047)	

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

Appendix D. Size of Banks Acquired by Treatment Group



Appendix E. T-Tests

Table 10: T-Test: Treatment vs. Control Groups

Variable	Treatment Mean	Control Mean	P-Value
Liabilities to Assets	88.705	88.856	0.462
Intangible Assets to Assets	1.850	2.073	**0.005**
Net Charge-Offs to Loans	0.383	0.394	0.713
Net Operating Income to Assets	1.952	1.357	0.022
Yield on Earning Assets	4.761	5.231	**0.00**
Urban Location	0.793	0.890	**0.00**

Appendix F. Code (R Programming Language)

```
# Load necessary libraries
library(readxl) # Library used to import excel files
library(aod) # Library used for the logit model analysis
library(ggplot2) # Library that supports other libraries
library(sjPlot) # Library used to create correlation matrix
library(stargazer) # Library used to create tables with regression results
library (writexl) # Library used to export R dataframes to Excel files

# Import and display excel sheet "entriesexits2003-2017.xlsx"
# Which details all entries and exits to FDIC insurance from 2003-2017
exit.and.entry <- read_excel("~/Downloads/F18/Thesis Data Files/entriesexits2003-2017.xlsx")
```

```
# Import and display excel sheet "QuarterlyThesisData.culled.xlsx"
# Which details quarterly SDI reports for all FDIC reporters 2003-2017
QuarterlyData <- read_excel("~/Downloads/F18/Thesis Data
Files/QuarterlyThesisData.culled.xlsx")

assetChange <- read_excel("~/Documents/Thesis Data Files/assetChange.xlsx")

# Create and display a data frame that merges closure data with all bank data
dataComplete <- merge(QuarterlyData, exit.and.entry, by=c("cert", "repdte"), all=TRUE)
dataComplete <- merge(dataComplete, assetChange, by=c("cert", "repdte", "asset"), all=TRUE)

# Set exit/de de novo dummies equal to 0 where R automatically set to NA
isna <- is.na(dataComplete)
iscol <- col(isna) %in% c(106, 107)
dataComplete[isna & iscol] <- 0
rm(isna, iscol)

# Create additional necessary variables
dataComplete$depoverasset <- dataComplete$dep / dataComplete$asset # Deposit share over assets
dataComplete$logasset <- log(dataComplete$asset) # Log of assets
dataComplete$intanratio100 <- dataComplete$intanratio * 100 # Increase intanratio for ease of
interpreting results
dataComplete$depoverasset100 <- dataComplete$depoverasset * 100 # Increase depoverasset for
ease of interpreting results
dataComplete$liaboverasset100 <- dataComplete$liaboverasset * 100 # Increase liabverasset for
ease of interpreting results
dataComplete$prox_asset <- dataComplete$asset * 0 # Initialize "prox_asset" to zero
dataComplete$merged <- ifelse(dataComplete$mna ==1, TRUE, FALSE) # Create a boolean for
whether a merger happened
# Create a "year" variable
for(i in 1:nrow(dataComplete)) {
  print(i)
  dataComplete$dateS[i] <- toString(dataComplete$repdte[i])
  dataComplete$year[i] <- substr(dataComplete$dateS[i],1,4)
}
dataComplete$quarter <- substr(dataComplete$dateS,6,7) # Create a variable that tells the
quarter of a given bank-quarter observation
dataComplete$merged_asset <- dataComplete$asset + dataComplete$prox_asset # Create a variable
that tells the total assets of the merged bank if a merger occurred (or the assets of the
original bank if no merger occurred)
dataComplete$ffr100 <- dataComplete$ffr * 100
dataComplete$merged_asset <- ifelse(dataComplete$mna == 1,
                                    dataComplete$asset + dataComplete$prox_asset, 0)

# Populate prox_asset with asset level of PROXIMATE_CERT in quarter repdte
for(i in 1:nrow(dataComplete)) {
  print(i)
  if(dataComplete$merged[i]) {
    subset_ind <- which(dataComplete$repdte == dataComplete$repdte[i])
    #View(subset_ind)
    subset <- dataComplete[subset_ind,]
    #View(subset)
```

```
    opts <- which(subset$cert == dataComplete$PROXIMATE_CERT[i])
    opts1 <-subset[opts,]
    if(nrow(opts1) == 1) {
      newval <- opts1$asset
        dataComplete$prox_asset[i] <- newval
    }
  }
}

# Assign banks to treatment and control groups
dataComplete$treat2 <- dataComplete$treat * 0
dataComplete$small <- dataComplete$cert * 0
dataComplete$large <- dataComplete$small * 0
dataComplete$small2 <- dataComplete$small * 0
dataComplete$large2 <- dataComplete$large * 0
relQ
k <- 0
for(i in relQ) {
  print (i)
  k <- k + 1
  print(k)
  if(dataComplete$year[i] == "2011" & dataComplete$quarter[i] == "03") {
    tempTreat <- ifelse(dataComplete$asset[i] >= 5000000 & dataComplete$asset[i] <= 8000000,
1, 0)
    tempTreat2 <- ifelse(dataComplete$asset[i] >= 5500000 & dataComplete$asset[i] <= 8500000,
1, 0)
    tempSmall <- ifelse(dataComplete$asset[i] >= 3000000 & dataComplete$asset[i] < 5000000, 1,
0)
    tempLarge <- ifelse(dataComplete$asset[i] > 8000000 & dataComplete$asset[i] <= 12000000,
1, 0)
    tempSmall2 <- ifelse(dataComplete$asset[i] >= 3000000 & dataComplete$asset[i] < 5500000,
1, 0)
    tempLarge2 <- ifelse(dataComplete$asset[i] > 8500000 & dataComplete$asset[i] <= 12000000,
1, 0)
    thisBank <- which(dataComplete$cert == dataComplete$cert[i])
    for(j in thisBank) {
      dataComplete$treat[j] <- tempTreat
      dataComplete$treat2[j] <- tempTreat2
      dataComplete$small[j] <- tempSmall
      dataComplete$large[j] <- tempLarge
      dataComplete$small2[j] <- tempSmall2
      dataComplete$large2[j] <- tempLarge2
    }
  }
}

# Code that assigns a variable for whether a bank acquired another bank in a given quarter
(t+1)
dataComplete$acqer <- dataComplete$mna * 0
for(i in c(1:nrow(dataComplete))) {
  print(i)
  if(dataComplete$mna[i] == 1) {
    subset_ind <- which(dataComplete$repdte == dataComplete$repdte[i]
```

```
                        & dataComplete$cert == dataComplete$PROXIMATE_CERT[i])
    dataComplete$acqer[subset_ind] <- 1
  }
}

# Get bins for chart in consolidation review
for(i in c(2005, 2008, 2011, 2014, 2017)) {
  print(i)
  print(length(which(dataComplete$year == i & dataComplete$quarter == "12" &
dataComplete$asset <= 1000000)))
  print(length(which(dataComplete$year == i & dataComplete$quarter == "12" &
dataComplete$asset > 1000000 & dataComplete$asset <= 10000000)))
  print(length(which(dataComplete$year == i & dataComplete$quarter == "12" &
dataComplete$asset > 10000000 & dataComplete$asset <= 50000000)))
  print(length(which(dataComplete$year == i & dataComplete$quarter == "12" &
dataComplete$asset > 50000000)))
}

#Distributional Statistics
# ffr
length(dataComplete$ffr100)
mean(dataComplete$ffr100, na.rm = TRUE)
sd(dataComplete$ffr100, na.rm = TRUE)
quantile(dataComplete$ffr100, probs = seq(0, 1, 0.05), na.rm = TRUE)
# assets
length(dataComplete$asset)
mean(dataComplete$asset, na.rm = TRUE)
sd(dataComplete$asset, na.rm = TRUE)
quantile(dataComplete$asset, probs = seq(0, 1, 0.05), na.rm = TRUE)
# liaboverasset100
length(dataComplete$liaboverasset100)
mean(dataComplete$liaboverasset100, na.rm = TRUE)
sd(dataComplete$liaboverasset100, na.rm = TRUE)
quantile(dataComplete$liaboverasset100, probs = seq(0, 1, 0.05), na.rm = TRUE)
# intanratio100
length(dataComplete$intanratio100)
mean(dataComplete$intanratio100, na.rm = TRUE)
sd(dataComplete$intanratio100, na.rm = TRUE)
quantile(dataComplete$intanratio100, probs = seq(0, 1, 0.05), na.rm = TRUE)
# ntlnlsr
length(dataComplete$ntlnlsr)
mean(dataComplete$ntlnlsr, na.rm = TRUE)
sd(dataComplete$ntlnlsr, na.rm = TRUE)
quantile(dataComplete$ntlnlsr, probs = seq(0, 1, 0.05), na.rm = TRUE)
# noijy
length(dataComplete$noijy)
mean(dataComplete$noijy, na.rm = TRUE)
sd(dataComplete$noijy, na.rm = TRUE)
quantile(dataComplete$noijy, probs = seq(0, 1, 0.05), na.rm = TRUE)
# intincy
length(dataComplete$intincy)
mean(dataComplete$intincy, na.rm = TRUE)
sd(dataComplete$intincy, na.rm = TRUE)
```

```
quantile(dataComplete$intincy, probs = seq(0, 1, 0.05), na.rm = TRUE)

# Create a correlation matrix of chosen variables
sjt.corr(dataComplete[,c("ffr", "logasset", "liaboverasset100", "intanratio100",
                         "ntlnlsr", "noijy", "intincy", "inMSA", "post", "cb")],
file="sjt_corr.doc")

# Convert logit coefficients into probabilities
converttoprob <- function(logit) {
  odds <- exp(logit)
  probMNA <- odds / (1 + odds)
  return (probMNA)
}

# Full merger and acquisition regression with full interaction terms
mnaFinal <- glm(mna ~ ffr100 + logasset + liaboverasset100 +
                  intanratio100 + ntlnlsr + noijy + intincy +
                  inMSA + logasset*post + liaboverasset100*post +
                  intanratio100*post +
                  ntlnlsr*post + noijy*post + intincy*post + inMSA*post + logasset*cb +
liaboverasset100*cb +
                  intanratio100*cb + ntlnlsr*cb + noijy*cb + intincy*cb + inMSA*cb +
                  logasset*post*cb + liaboverasset100*post*cb +
                  intanratio100*post*cb +
                  ntlnlsr*post*cb + noijy*post*cb + intincy*post*cb + inMSA*post*cb,
                data = dataComplete, family = "binomial")
summary(mnaFinal)
probMNA <-converttoprob(coef(mnaFinal))
probMNA

# Full failure regression, no interaction terms
failFinal <- glm(failure ~ ffr100 + logasset + liaboverasset100 +
                   intanratio100 + ntlnlsr + noijy + intincy + inMSA,
                  data = subset.data.frame(dataComplete), family = "binomial")
summary(failFinal)
probfail <-converttoprob(coef(failFinal))
probfail

# Full merger and acquisition regression with full interaction terms
acqerFinal <- glm(acqer ~ ffr100 + logasset + liaboverasset100 +
                  intanratio100 + ntlnlsr + noijy + intincy +
                  inMSA + logasset*post + liaboverasset100*post +
                  intanratio100*post +
                  ntlnlsr*post + noijy*post + intincy*post + inMSA*post,
                data = dataComplete, family = "binomial")
summary(acqerFinal)
stargazer(acqerFinal, title="Acquirer Results with Time Period Interaction Terms", align=TRUE)
probacqer <-converttoprob(coef(acqerFinal))
probacqer

# What percent of acquirers were community banks in pre/post periods?
length(which(dataComplete$acqer == 1 & dataComplete$cb == 1 & dataComplete$post == 0)) /
length(which(dataComplete$acqer == 1 & dataComplete$post == 0))
```

```
length(which(dataComplete$acqer == 1 & dataComplete$cb == 1 & dataComplete$post == 1)) /
length(which(dataComplete$acqer == 1 & dataComplete$post == 1))


# Failure logits for Appendix - with post
failxpost <- glm(failure ~ ffr100 + logasset + liaboverasset100 +
                   intanratio100 + ntlnlsr + noijy + intincy +
                   inMSA + logasset*post + liaboverasset100*post +
                   intanratio100*post +
                   ntlnlsr*post + noijy*post + intincy*post + inMSA*post,
                 data = subset.data.frame(dataComplete), family = "binomial")
summary(failxpost)
stargazer(failxpost, title="Failure Results with Time Period Interaction Terms", align=TRUE)
probfail2 <-converttoprob(coef(failxpost))
probfail2

#with cb
failxcb <- glm(failure ~ ffr100 + logasset + liaboverasset100 +
                   intanratio100 + ntlnlsr + noijy + intincy +
                   inMSA +
                   logasset*cb + liaboverasset100*cb +
                   intanratio100*cb + ntlnlsr*cb + noijy*cb + intincy*cb + inMSA*cb,
                 data = subset.data.frame(dataComplete), family = "binomial")
summary(failxcb)
stargazer(failxcb, title="Failure Results with Community Bank Interaction Terms", align=TRUE)
probfail3 <-converttoprob(coef(failxcb))
probfail3

failxpostxcb <- glm(failure ~ ffr100 + logasset + liaboverasset100 +
                   intanratio100 + ntlnlsr + noijy + intincy +
                   inMSA + logasset*post + liaboverasset100*post +
                   intanratio100*post +
                   ntlnlsr*post + noijy*post + intincy*post + inMSA*post + logasset*cb +
liaboverasset100*cb +
                   intanratio100*cb + ntlnlsr*cb + noijy*cb + intincy*cb + inMSA*cb +
                   logasset*post*cb + liaboverasset100*post*cb +
                   intanratio100*post*cb +
                   ntlnlsr*post*cb + noijy*post*cb + intincy*post*cb + inMSA*post*cb,
                 data = subset.data.frame(dataComplete), family = "binomial")
summary(failxpostxcb)
stargazer(failxpostxcb, title="Failure Results with Time Period and Community Bank Interaction
Terms", align=TRUE)
probfail4 <-converttoprob(coef(failxpostxcb))
probfail4

# Create a table reporting all merger and acquisition regression results
stargazer(mna1.1, mna1.2, mna1.3, mna1.4, mna1.5, mna1.6,
          mna1.7, mna1.8, mna1.9,
          title="Merger and Acquisition Results, All Regressions", align=TRUE)

# Create a subset of data with only treat and control groups
subDataComplete <- subset.data.frame(dataComplete, treat2 == 1 | small2 == 1 | large == 1)
# Remove those banks that leave sample
```

```
subDataComplete <- subset.data.frame(subDataComplete, cert != 58878 & cert != 18261 & cert !=
18538)
subDataComplete <- subset.data.frame(subDataComplete, cert != 680 & cert != 21726 & cert !=
19553)
subDataComplete <- subset.data.frame(subDataComplete, cert != 58656 & cert != 58979 & cert !=
30559)
subDataComplete <- subset.data.frame(subDataComplete, cert != 18169 & cert != 19919 & cert !=
16049)
subDataComplete <- subset.data.frame(subDataComplete, cert != 986 & cert != 30890 & cert !=
34590)
subDataComplete <- subset.data.frame(subDataComplete, cert != 35453 & cert != 14318 & cert !=
28994)
subDataComplete <- subset.data.frame(subDataComplete, cert != 57529 & cert != 32158 & cert !=
58596)
subDataComplete <- subset.data.frame(subDataComplete, cert != 22599 & cert != 58303 & cert !=
15504)
subDataComplete <- subset.data.frame(subDataComplete, cert != 32102 & cert != 58177 & cert !=
35575)
subDataComplete <- subset.data.frame(subDataComplete, cert != 18113 & cert != 20626 & cert !=
20852)
subDataComplete <- subset.data.frame(subDataComplete, cert != 24107 & cert != 7414 & cert !=
29979)
subDataComplete <- subset.data.frame(subDataComplete, cert != 33778 & cert != 57833 & cert !=
6784)

# Assign large and small control group dummies for clarity in testing
#subDataComplete$large <- ifelse(subDataComplete$asset > 6500000 & subDataComplete$treat == 0,
1, 0)
#subDataComplete$small <- ifelse(subDataComplete$asset < 6500000 & subDataComplete$treat == 0,
1, 0)

#find proportions of variables
sum(subDataComplete$treat2)
mean(subDataComplete$treat2)
sum(subDataComplete$small2)
mean(subDataComplete$large)
mean(subDataComplete$post)
mean(subDataComplete$mna)
mean(subDataComplete$acqer)

# Get number of mergers and acquisitions in each year for common trends assumption
# for treatment group
for(i in c(2003:2008, 2011:2017)) {
  threeQ1 <- which(subDataComplete$year == i &
                     subDataComplete$treat== 1
                   & subDataComplete$acqer == 1
  )
  print(length(threeQ1))
}
# for small control group
for(i in c(2003:2008, 2011:2017)) {
  threeQ1 <- which(subDataComplete$year == i &
                     subDataComplete$small== 1
```

```
                   & subDataComplete$acqer == 1
  )
  print(length(threeQ1))
}
#for large control group
for(i in c(2003:2008, 2011:2017)) {
  threeQ1 <- which(subDataComplete$year == i &
                     subDataComplete$large== 1
                   & subDataComplete$acqer == 1
  )
  print(length(threeQ1))
}

# Baseline DND model, no control vars
mnaDND <- glm(acqer ~ treat2 + post + treat2*post, data = subDataComplete)
summary(mnaDND)
probDND <-converttoprob(coef(mnaDND))
probDND

# DND model for acquirers with complete control vars
mnaDND2 <- glm(acqer ~ treat2 + post + treat2*post + logasset + liaboverasset100 +
                intanratio100 + ntlnlsr + noijy + intincy + inMSA, data = subDataComplete)
summary(mnaDND2)
probDND2 <-converttoprob(coef(mnaDND2))
probDND2
```

Works Cited

Adams, Robert M. and Jacob Gramlich. 2016. "Where Are All the New Banks? The Role of Regulatory Burden in New Bank Formation." *Review of Industrial Organization,* 48 (2): 181-208.

Bishaw, Alemayehu and Kirby G. Posey. 2016. "A Comparison of Rural and Urban America: Household Income and Poverty." U.S. Census Bureau, Social, Economic, and Housing Statistics Division.

Board of Governors of the Federal Reserve System (US). 2018. "Effective Federal Funds Rate [FEDFUNDS]." *FRED, Federal Reserve Bank of St. Louis*.

Board of Governors of the Federal Reserve System (US). 2018. "Real Gross Domestic Product [A191RL1A225NBEA]." *FRED, Federal Reserve Bank of St. Louis*.

Boyd, John H. and Stanley L. Graham. 1991. "Investigating the Banking Consolidation Trend." *Federal Reserve Bank of Minneapolis Quarterly Review Spring*, 1991: 3-15.

Canbas, Serpil, Altan Cabuk, and Suleyman Bilgin Kilic. 2005. "Prediction of Commercial Bank Failure via Multivariate Statistical Analysis of Financial Structures: The Turkish Case." *European Journal of Operational Research,* 166 (2): 528-546.

Cole, Rebel A. and Lawrence J. White. 2012. "Déja` Vu All Over Again: The Causes of US Commercial Bank Failures This Time Around," J*ournal of Financial Services Research,* 42(1): 5-29.

Curry, Timothy and Lynn Shibut. 2000. "The Cost of the Savings and Loan Crisis: Truth and Consequences." *FDIC Banking Review,* 2000 13(2): 26-35

DeYoung, Robert, Douglas D. Evanoff, and Philip Molyneux. 2009. "Mergers and Acquisitions of Financial Institutions: A Review of the Post-2000 Literature." *Journal of Financial Services Research,* 36 (2): 87-110.

DeYoung, Robert and Gökhan Torna. 2013. "Nontraditional Banking Activities and Bank Failures During the Financial Crisis." *Journal of Financial Intermediation,* 22(3): 397-421.

Dharmapala, Dhammika. 2016. "Estimating the Compliance Costs of Securities Regulation: A Bunching Analysis of Sarbanes-Oxley Section 404(B)." *University of Chicago Coase-Sandor Institute for Law & Economics* Research Paper.

Dodd-Frank Wall Street Reform and Consumer Protection Act, Pub. L. No. 111-203, 124 Stat. 1376 (codified as amended at 12 U.S.C. § 5301 et seq. (2018)).

Economic Growth, Regulatory Relief, and Consumer Protection Act, Pub. L. No. 115-174, § 401, 132 Stat. 1296 (codified at 12 U.S.C. § 5365 (2018)).

FDIC Applications Staff in the Department of Risk Management and Supervision. 2016. "De Novo Banks: Economic Trends and Supervisory Framework." *Supervisory Insights*, Summer 2016.

Federal Deposit Insurance Corporation (FDIC). 2018. "Changes in Number of Institutions; FDIC-Insured Commercial Banks; US and Other Areas." *Historical Statistics on Banking*.

Federal Deposit Insurance Corporation (FDIC). 2018. "Number of Institutions, Branches and Total Offices; FDIC-Insured Commercial Banks; United States (50 States and DC)." *Historical Statistics on Banking*.

Frank, Barney. 2016. "The Legislation Is Doing What It Was Designed to Do." *New York Times*.

Hannan, Timothy H., and Steven J. Pilloff. 2009. "Acquisition Targets and Motives in the Banking Industry." *Journal of Money, Credit and Banking*, 41 (6): 1167-1187.

Hensarling, Jeb. 2015. "Dodd-Frank's Unhappy Fifth Birthday: Remarks from Chairman Jeb Hensarling." American Enterprise Institute.

Hou, David, and Missaka Warusawitharana. 2018. "Effects of Fixed Nominal Thresholds for Enhanced Supervision," *FEDS Notes. Washington: Board of Governors of the Federal Reserve System*, July 19, 2018.

Hughes, Joseph P., Loretta J. Mester, and Choon-Geol Moon. 2001. "Are Scale Economies in Banking Elusive or Illusive? Evidence Obtained by Incorporating Capital Structure and Risk-Taking into Models of Bank Production." *Journal of Banking and Finance*, 25: 2169-2208.

Jacobs, Karen. 2018. "What's Behind the Upswing in Bank Mergers?" *Federal Reserve Bank of Atlanta, Economy Matters*, February 8, 2018.

Jagtiani, Julapa. 2008. "Understanding the Effects of the Merger Boom on Community Banks." *Federal Reserve Bank of Kansas City, Economic Review*, 93 (2): 29-48.

Kowalik, Michael, Troy Davig, Charles S. Morris, and Kristen Regehr. 2015. "Bank Consolidation and Merger Activity Following the Crisis." *Federal Reserve Bank of Kansas City Economic Review, First Quarter, 2015*: 31-49.

Lee, Yan and Chiwon Yom. 2016. "The Entry, Performance, and Risk Profile of De Novo Banks." *FDIC Center for Financial Research*, Working Paper 2016-03, April 2016.

Lopez, Jose A. 1999. "Using CAMELS Ratings to Monitor Bank Conditions." *Federal Reserve Bank of San Francisco Economic Letter*, 1999-19.

Lu, Wenling and David A. Whidbee. 2016. "US Bank Failure and Bailout During the Financial Crisis." *Journal of Financial Economic Policy*, 8(3): 316-347.

Lux, Marshall, and Robert Greene. 2015. "The State and Fate of Community Banking." *Harvard Kennedy School Mossavar-Rahmani Center for Business & Government*, M-RCBG Associate Working Paper Series no. 37.

Lux, Marshall and Robert Greene. 2016. "Dodd-Frank Is Hurting Community Banks." *The New York Times*.

McAllister, Patrick H., and Douglas McManus. 1993. "Resolving the Scale Efficiency Puzzle in Banking." *Journal of Banking and Finance*, 17: 389-405.

McLaughlin, Patrick, Oliver Sherouse, and Daniel Francis. 2017. "Dodd-Frank Is One of the Biggest Regulatory Events Ever." Mercatus Center, George Mason University.

Meyer, Andrew P. 2018. "Market Concentration and Its Impact on Community Banks." *Federal Reserve Bank of St. Louis Regional Economist*, First Quarter 2018.

Nichols, Rob. 2016. "Yes, Community Banks Are Struggling Under Dodd-Frank." *Politico*.

Nicoletti, Allison, Hailey Ballew, and Michael Iselin. 2017. "Regulatory Asset Thresholds and Acquisition Activity in the Banking Industry." Unpublished.

Office of the Comptroller of the Currency. 1988. "Bank Failure: An Evaluation of the Factors Contributing to the Failure of National Banks." *Comptroller of the Currency, Administrator of National Banks*, Washington.

Onji, Kazuki. 2009. "The Response of Firms to Eligibility Thresholds: Evidence from the Japanese Value-added Tax." *Journal of Public Economics*, 93(5): 766–775.

Peirce, Hester, Ian Robinson, and Thomas Stratmann. 2013. "How Are Small Banks Faring Under Dodd-Frank?" *Mercatus Center, George Mason University*, Working Paper no. 14-05.

Stackhouse, Julie. 2018. "The ABCs of CAMELS." *Federal Reserve Bank of St. Louis*.

St. Clair, Travis. 2016. "How Do Nonprofits Respond to Regulatory Thresholds: Evidence From New York's Audit Requirements." *Journal of Policy Analysis and Management*, 35(4): 772.

Tracy, Ryan. 2017. "U.S. Banking Industry Annual Profit Hit Record in 2016." *Wall Street Journal*.

Vallabhaneni, Pratin. 2017. "The Reemergence of De Novo Bank Charters." Arnold & Porter.

Wheelock, David C., and Paul W. Wilson. 2000. "Why Do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions." *The Review of Economics and Statistics*, 82 (1): 127-138.

Wheelock, David C., and Paul W. Wilson. 2001. "New Evidence on Returns to Scale and Product Mix Among U.S. Commercial Banks." *Journal of Monetary Economics*, 46: 653-674.

Wheelock, David C. and Paul W. Wilson. 2012. "Do Large Banks Have Lower Costs? New Estimates of Returns to Scale for U.S. Banks." *Journal of Money, Credit, and Banking,* 44 (1): 171-199.

Witkowsky, Rachel. 2018. "Floodgates Open? De Novo Applications Surge at FDIC." *American Banker*.