IMPACT OF FIRM-LEVEL BANK

CONSOLIDATION ON

MORTGAGE LOAN AVAILABILITY

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Abstract: Since the economic crisis of 2008, the number of U.S. banks has declined by an average of 4.5% per year. Factors in bank decline include consolidation due to increased competition from nonbank entities, technological shifts, changing consumer preferences, and increasing regulatory requirements. Recent research concludes that bank consolidation creates small business lending credit gaps. By examining the impact of bank consolidation on the potential credit gaps in mortgage lending, I add to the bank consolidation literature and its potential consumer consequences in a highly regulated and competitive industry. I examine bank consolidation effects on (1) the quantity and value of loans originated, (2) the average mortgage loan value, (3) the percent of bank mortgage loan focus to total loans, (4) the influence of acquirers' loan specialization on loan originations, and (5) the influence of acquirers' headquarter locations on loan originations. Using a sample size of 1,562 Home Mortgage Disclosure Act of 1974 (HMDA) and FDIC Bank combinations for the periods 2010 through 2020, I test nine hypotheses using univariate analysis and regression models. Of the nine hypotheses, and contrary to my predictions, Hypotheses 3 and 4 results indicate a significant positive relationship between bank consolidation effects and the likelihood of lower average mortgage loan amounts and increased mortgage lending to total lending post-consolidation. Although the remainder of the hypotheses tests did not render significant results, the results prompt avenues of future research in relative size disparities in target and acquiring bank consolidations.

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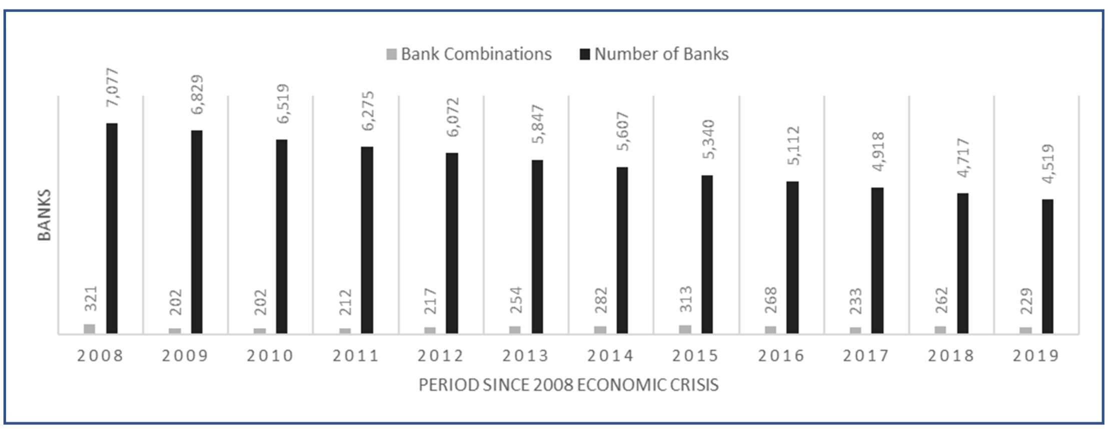
CHAPTER I

INTRODUCTION AND RESEARCH PROBLEM

Since the economic crisis of 2008, the number of U.S. commercial banks has declined by 36%, representing a consolidation of 2,558 banks with an average of 250 bank mergers a year or 4.45% of FDIC insured banks in operation as described in Figure 1.

FDIC Annual Historical Bank Data



The steady decline in the number of U.S. banks through consolidation is driven by a myriad of factors that include significant industry deregulation prompted in part by bank failures and waning consumer trust stemming from the economic crisis of 2008. Bank consolidations were also facilitated by increased competition from nonbank entities that leveraged technological shifts adapting to changing consumer preferences. While extant literature examines the impact of consolidations on consolidated bank fundamentals and investor returns, relatively little research focuses on how bank consolidations affect the availability of credit in the markets they service.

Recently, Jagtiani and Maingi (2018) concluded that bank consolidations have a profoundly negative effect on the availability of small business loans within the counties served, thus creating small business lending credit gaps. Along with other consolidation literature, their results elicit concerns that bank consolidations may create similar lending credit gaps at the consumer level, specifically with regard to mortgage loan availability at the bank firm-level.

The magnitude and implication of mortgage lending on the U.S. economy and communities cannot be overstated. In 2020, for example, $11.05 trillion in mortgages were outstanding with another $1.9 trillion mortgages funded with mortgage debt, making up approximately 70% of all household debt. However, there continues to be inequality in the extension of mortgage lending by banks in rural areas, with the exception of community banks. In an article by the Brookings Institution (2018), mortgage lending in rural communities by community banks and credit unions make up 20% of all mortgage loans originating in the U.S. and 33% of mortgages in rural areas. In 2016, U.S. rural communities made up 23% of the total U.S. population and 21% of people of color, a market segment that has historically been underserved (Williams et al., 2005). Mortgage lending is also the largest asset class among community banks that service rural areas. As banks of various sizes and geographical locations continue to consolidate, the question is raised as to potential changes in their respective mortgage loan portfolios and consequences to the communities they serve. Regulators are also questioning the decline in mortgage lending trends among banks and the potential impacts to the people they serve. In the FEDS Notes (Bhutta et al., 2017), data from the Housing Mortgage Disclosure Act (HMDA) for the period of 2010 through 2016 show declines from all banks in mortgage lending, both in low- and moderate-income households (LMIs) in recent years. Another concerning trend described is the decline in originations of loans insured by the Federal Housing Administration (FHA) by banks that averaged 37% market share in 2010, falling to 12% by 2016. The question for borrowers is whether the drop in FHA and LMI household mortgage lending leads to limited access to credit if not offset by other lenders to the degree of reduced mortgage lending of the largest banks (Bhutta et al., 2017). The FDIC's recent community banking study is also interested in the decline of community banks trending away from residential mortgages and towards commercial real estate loans (CREs), and small business lending. CREs as a proportion of community bank loan portfolios grew from 38% in 2011 to 40% in 2019. Although on the surface the change may not appear significant, when contrasted with the growth in market share from 51% to 58% over the same period, it is evident that community banks are changing their loan portfolio strategy. Along with the growth in CREs, small business lending originations by community banks are also growing with increases from 38% in 2012 to 46% in 2019, while noncommunity banks increased small business lending from 54% to 62% in the same period (FDIC, 2020). In contrast, community banks appear to be moving away from mortgage lending as the growth of community bank mortgage originations fell from a high of 6% annual growth in 2014 to 3% in 2019 (FDIC, 2020). The authors of the FDIC 2020 community banking report suggest the rationale for the decline in mortgage lending is due in part to increased regulatory costs, changes in financial and information technology, as well as the commoditization of retail lending through increased competition from nonbank entities.

Despite the research investigating the relationship between bank consolidation and small business lending, there appears to be a gap in the literature regarding the impacts of bank consolidation on the availability of mortgage loans. While bank mortgage loan portfolios secured by (1-4 family) residential properties constituted 59% of total real estate loans in 2010, they now make up 50% of total real estate loans originated (FDIC, 2019). The purpose of this research is to test empirically the effects of bank consolidation at the firm-level post- 2008 economic crisis, specifically on the availability of mortgage loans (1-4 family) to determine the likelihood of credit gaps in the communities they serve. My motivation to research the dynamics of bank consolidation and mortgage lending extends beyond the empirical studies cited throughout my research, as I have direct experience as a former financial analyst at the Resolution Trust Corporation (RTC). The RTC was a temporary federal agency enacted from 1989 to 1995 to resolve the savings and loan crisis of the 1980s. The agency was tasked with cleaning up 747 failed financial institutions with total assets of $394 billion, the largest collapse of U.S. financial institutions since the Great Depression (Investopedia, 2020). I was part of a team responsible for the dissolution of hundreds of properties and associated mortgages; thus, I learned firsthand the effects of overzealous mortgage lending and the pitfalls of increased competition. Once again, I am motivated in recent years to better understand the dynamics of bank consolidations and mortgage lending.

My research applies a time fixed-effects event study framework to examine changes in the quantity, amounts, per-loan amounts, and percent of mortgage loan concentrations to total loans around bank consolidation events. In addition, I also investigate the sensitivity of the above changes to the relative location of the acquiring and target banks as well as the influence an acquiring bank's mortgage loan focus plays post consolidation. I assert that as banks consolidate, the newly created combined entity originates fewer mortgage loans at higher per-loan origination amounts to the counties in which they operate, potentially leading to credit gaps. However, an argument can also be made that some of the catalysts for bank consolidation such as economies of scale, technological efficiencies, and loan portfolio risk mitigation benefit the consumer and thus reduce potential credit gaps. By analyzing the relationship of banking consolidation and mortgage loans over the period of 2011 through 2019, I believe my findings contribute to extant research and fill the apparent literature gap, benefiting academia by testing financial intermediation theory, which is based on transaction and asymmetric information from institutions that take deposits and distribute funds to firms (Allen & Santomero, 1998). Additionally, my findings provide valuable insight to banking industry policy makers regarding mortgage availability for consumers.

The research is structured into six chapters. Chapter 1 provides an introduction and justification for the research. Chapter 2 presents a review of extant research in bank consolidation as well as bank lending after the 2008 economic crisis. Chapter 3 describes the hypotheses formulation of nine hypotheses for empirical study and respective economic rationale. Chapter 4 includes a description of the dataset, empirical methodologies, and research design. Chapters 5 describes model results along with a research conclusion.

CHAPTER II

LITERATURE REVIEW

The phenomenon of bank consolidation has been examined through a variety of lenses that include determining factors such as changes in banking regulations, increased competition from nontraditional banks, and technological advancements. So as not to overwhelm the reader with the broader literature on bank consolidation, in this section I confine my review to studies closely related to the research question I seek to address.

Although there is an apparent gap in the literature focused on bank consolidations and mortgage lending, parallels of bank consolidation and small business lending research provide insight into mortgage lending as many banks typically hold both forms of credit vehicles in their loan portfolios. Similarities of small business and mortgage lending include a declining portfolio composition of both types of loans to total assets. In a study by the FDIC, over the periods of 1984 through 2011, on a consolidated basis (including community and noncommunity banks), the proportion of mortgage lending to total assets fell from 19% to 17%, while business lending fell from 16% to 10% (FDIC, 2020). Another similarity of small business and mortgage lending is the increasing competition from nonbanks that leverage technology to expedite and simplify the lending process paramount in customer satisfaction. A McKinsey 2018 retail banking customer experience survey identified three top reasons for choosing a lender: ranked first was exceptional customer service, followed by best interest rate, and existing relationship. In conjunction, the three top improvements desired by customers were: getting things right the first time; pre-approval within 24 hours; and quick, clear, 24/7 status (Cope et al., 2020). Although small business and mortgage lending similarities deviate in the types of credit users either by consumer or organization, they both draw on common bank infrastructure that contributes to the profitability and viability of banks.

I identified three studies, Berger et al. (1998), Peek and Rosengren (1998), and Jagtiani and Maingi (2018) that empirically test the relationships of bank consolidation and small business bank lending. Bank consolidation (M&A) and small business loan studies address the concern of policy makers and banking scholars regarding the supply of credit or potential credit gaps to small businesses related to bank asset size, location, or lending philosophy (relationship or transactional). As postulated by Berger et al. (1998), the body of research on bank consolidation and its effect on small business lending provides a mixed picture, thus prompting the question of whether consolidation of U.S. banks substantially reduces the supply of credit to small business. By examining the dynamic net impacts of bank consolidation and small business lending, the authors measure the effects of consolidation on lending by other banks in the same local markets. The study supplements extant literature that focuses solely on static comparisons and conclusions of consolidation and small business lending by measuring the static, restructuring, and direct effects (also defined as dynamic effects) for over 6,000 U.S. bank consolidations from 1970 to 1990. The literature includes research by Peek and Rosengren (1996, 1998) that finds consolidations between two smaller banking institutions often leads to an increase in small business lending. Weston and Strahan (1996) and Strahan and Weston (1998) also test the relationship of small business lending pre- and post-consolidation and find that regardless of bank size differences, there is no clear effect on small business lending. Lastly, Walraven (1997) finds that after a bank consolidation, the level of small business lending tends to revert to the level of the surviving bank.

The static effect is designed to capture pre-consolidation and post-consolidation balance sheets focused on the quantity of available small business loans. A restructuring effect is defined as the change in firm focus impacted by changes in size, financial condition, or competitive position that occur post-consolidation. For example, if a $500 million bank acquires a $300 million bank, the restructuring effect might result in a consolidated $600 million bank rather than a combined $800 million bank. Lastly, the direct effect reflects the potential change in lending by refocusing firm attention toward or away (due to changes in lending policy) from small business lending net of restructuring and static effects. The results of the study indicate that the effect of bank consolidation on small business lending is more complex than previously thought. When isolated, the static effect of bank consolidation is associated with considerable negative impact on small business lending. By including external reactions of other banks, the decline in small business lending is somewhat offset. The restructuring and direct effects appear to have a limited impact on small business lending. Another key finding of the analysis is that absolute and relative asset sizes of consolidating banks impact the level of small business lending. Consolidation of small- and medium-asset sized banks appear to increase the level of small business lending. In contrast, larger bank consolidations are associated with decreases in small business lending. Further, the research by Jagtiani and Lemieux (2016) also identifies a relationship between the volume of small business lending and the relative sizes of participating banks. Small business lending research includes results of the 2008 economic crisis and its impact on the declining volume of small business lending by banking institutions.

Coupled with bank consolidation and the 2008 economic crisis, one might speculate that the reduced volume of small business lending is a manifestation of the two factors alone. However, the downward trend began at least a decade before the 2008 economic crisis, further demonstrating the increasingly dynamic competitive environment and its impact on small business lending. The competitive environment includes the entry of nonbank lenders such as credit unions, independent mortgage companies, and Fintech organizations that compete with sophisticated technology that facilitates faster processing times, automated applications, and limited required financial supporting documentation. Small banks, those who have access to better credit information gathered from activities through a customer’s deposit account as well as a better lending relationship due to the organizational structure of small banks, are found to perform better than larger banks in the small business lending market, while large banks perform better with credit card lending and other standardized loans (Carter & McNulty, 2005).

Peek and Rosengren (1998) investigate the effects of bank consolidation on small business lending. Similar to the research of Berger et al. (1998), the period of rapid bank consolidation raised concerns by researchers and policy makers that such industry consolidation could potentially reduce credit availability to small businesses as banks were a traditional source of fulfilling credit needs. Further compounding the concerns was that during the years of rapid bank consolidation, large business loans grew faster than small business loans. Additionally, small business lending grew faster at small banks relative to large banks. Lastly, they determined that a bank's loan portfolio share of small business loans is often inversely related to the total asset size of the institution. Over a three-year period, 1993 through 1996, the authors documented the business loan growth rate from the respective bank's June call report submitted to the FDIC. In all, the data included 872 consolidation observations with the following breakdown: 261 observations reflect acquirers of less than $100 million in assets, 196 observations of acquirers with greater than $100 million but less than $300 million in assets, and 144 observations of acquirers with greater than $300 million in assets. The authors find support for their hypothesis that acquirers often recast the target bank small business loan portfolio into the acquirer's pre-consolidation portfolio image. Furthermore, with changes in small business lending, subsequent consolidation is dependent on the acquirer's asset size, the allocation of small business loans in the loan portfolio of the acquirer, and the degree to which the acquiring bank's commitment to small business lending as a specialty prevailed. All factors affected the consolidated bank's willingness to engage in small business lending.

In a study that aligns with both Berger et al. (1998) and Peek and Rosengren (1998), Jagtiani and Maingi (2018) investigate the impact on local small business lending as a result of the shrinking banking sector by focusing solely on community banks. Small business lending in their study is measured from the perspective of both the acquirers' and targets' operations before and after consolidation. The study's motivation is to better understand the interplay among community banks' comparative advantages in small business lending, their local presence, and their involvement in mergers and acquisitions. Specifically, the authors use bank mergers as a shock to the community banking sector to identify firm-level and county-level responses in local small business lending markets. The analysis is based on data of all bank mergers during 2002 through 2014 that include U.S. community bank targets. Along with the merger data set, data on the quantity of small business loan originations by banks in each county by year for the periods 2001 through 2015 was derived from quarterly call reports submitted to the FDIC. The resulting data is bifurcated by two different target community bank definitions: $1 billion and $10 billion asset thresholds for both pre- and post-consolidation with merger observations of 477 and 511, respectively. By looking deeper into the geographic location of changes in small business lending, the authors find a decrease in small business loan funding when a consolidation occurred in an acquisition target's county. The result is even stronger when the acquiring bank is a large bank. However, when a consolidation occurs in an acquirer's county, small business loans increase, suggesting that the impact of community banks mergers are dependent on bank operations prior to consolidation.

As addressed in the preceding literature review, there appears to be a gap in the literature regarding bank consolidation post-2008 economic crisis and its effect on bank mortgage loan portfolios. The studies by Berger and colleagues (1998), Peek and Rosengren (1998), and Jagtiani and Maingi (2018) provide a paradigm for both bank consolidation and small business lending. My hypotheses, described in Chapter III, builds on similar analytical logic of previous research on bank consolidation but substitutes small business lending with mortgage lending to determine any potential consumer mortgage loan credit gaps.

CHAPTER III

HYPOTHESIS FORMULATION

My research tests the relationship between bank consolidation and the quantity, aggregate amount, per-loan amount, and percent of mortgage lending concentration by bank firm. In addition, I test the relational effects of bank target location and bank acquirer loan specialization to determine their significance on the availability of mortgage loan originations.

The rationale to pursue consolidation with another bank is typically to sell more services and products to customers as well as to improve the credit management of the combined firm. Focarelli and Panetta (2002) describe the justification of bank consolidations as prompted by cost reductions and growth opportunities. They conclude that bank consolidations aimed at increasing enterprise value are often achieved by improving the loan quality of the combined loan portfolio. One such strategy is to improve loan quality is by reducing the level of small business lending or limiting the ratio of bad loans to total loans. Research by Wheelock and Wilson (2000) on the determinants of U.S. bank failures and acquisitions also points to a higher probability of failure and potential for acquisition for banks maintaining relatively illiquid, low-quality assets.

Ntiamoah et al. (2014) investigate loan default rates and firm profitability and conclude that defaults arise from poor management procedures and improper appraisal by credit officers. They also reference the Five Cs, (Character, Capacity, Capital, Conditions, and Collateral) that are core to loan optimization. Some of the bad credit policies they describe include lenders trying to ignore conditions such as high loan-to-value ratios as well as historically low loan loss reserves that function as contingencies for loan exposure. Loan exposure is increased if banks ignore the borrower's capacity by following the competitive lending behaviors of competitors that erode credit standards to maintain profitability.

Increased bank risk and subsequent reduction in profitability due to loan exposure may also drive further bank consolidation and affect future lending practices post-consolidation. Li's (2005) research describes an increasing mortgage loan-to-value ratio (LTV), a metric that affects the underwriting standards for the majority of mortgage purchasers such as Fannie Mae and Freddie Mac, who are instrumental in both the underwriting and securitizations of mortgage loans. He indicates that the average LTV in 1984 was 26%; by 2001, it had increased to 35%. Today the average LTV is 84% (FHFA, 2019). Another indicator of bank loan exposure is derived by estimating the level of anticipated losses on loans due to defaults and nonpayment established by appropriate loan-loss reserves subject to market conditions. The economic research data from the Federal Reserve Bank of St. Louis on loan-loss reserves to total loans for all U.S. banks indicates a downward slide from a high of 4% in Q1 of 2010 to a low of 1% in Q4 of 2019. The lower levels of loan-loss reserves to total loans present an optimistic view of loan defaults and nonpayment. By limiting loan-loss reserves, a bank benefits with improved firm profitability in the short run but may later be required to expense loan defaults and nonpayment as they occur in the future, potentially decreasing firm profitability.

Bank firm profitability is derived from limited loan revenue streams that include conventional conforming mortgage loan originations. Recent research on trends in mortgage originations and servicing by the FDIC find that post-economic crises, banks lost approximately 32% market share in conventional conforming mortgage loan originations, down from 80% market share (FDIC Quarterly, 2019). They also find that nonbank mortgage originations grew steadily and now exceeds the volume and market share of bank mortgage originations. The drop in market share origination by banks is due in part to the increasing cost to originate and service mortgage loans as a result of post-crisis litigation for crisis-era legacy portfolios (FDIC Quarterly, 2019). The post-crisis litigation-associated fines and legal fees assessed on large banks reduced profitability on their mortgage loan portfolios with the unintended consequence of potentially deterring post-crisis mortgage originations. The study also notes that most nonbanks focus on mortgage lending as their core competence, placing banks at a disadvantage when developing application technologies aimed at streamlining and automating the origination process that contributes to the profit of mortgage loans. Large banks in particular are at a disadvantage in mortgage loan origination expenses as costs for corporate administration is on average three times as high as nonbanks. The greater overhead administrative expenses include providing efficient technology support for mortgage loan originations along with system costs not germane to mortgage lending but necessary for other elements to support their business. The trend of lower revenues and higher expenses handicap banks as they compete with nonbanks not burdened by higher infrastructure costs (Shoemaker, 2019). Further, a review by the Stratmor Group (Finnegan, 2019) found that since 2016 large banks lost on average $850 per mortgage loan, increasing to an average loss per mortgage loan of $4,803 in 2018. However, nonbanks or mortgage loan specialist also realized lower profits from $975 per loan in 2016 to $376 in 2018 but remained profitable. The critical driver in lower profitability is the high cost to originate a retail mortgage loan. In 2018, the average bank total per-loan expense was $13,628 compared to nonbank total per-loan expense of $10,097, or roughly 25% lower.

Mortgage loan costs include not only origination expenses but also loan servicing expenses. The mortgage origination and servicing trends identified by the 2019 FDIC quarterly report echo the expense trajectory of mortgage originations with the cost of loan servicing growing from $541 per loan in 2008 to $2,631 per loan in 2018 for both performing and nonperforming loans. In isolation, performing loans' service costs increased nearly threefold, and nonperforming loans saw an increase of more than fivefold (FDIC, 2020). Although banks continue to lose market share in conventional conforming and government loans to nonbanks, they have maintained and grown their market share of jumbo loans to over 80%. Jumbo loans values typically exceed $726,525 but vary from state to state. Unlike a conventional loan, jumbo loans cannot be purchased, guaranteed, or securitized by Fannie Mae or Freddie Mac and undergo more rigorous credit requirements compared to a conventional loan. Approval of jumbo loans require high credit scores, very low debt-to-income ratios, and down payments of roughly 10% to 15% of the total purchase price. Often the consumers of jumbo loans are a smaller segment than conventional loan consumers that tend earn between $250 to $500 thousand per year (Campisi, 2022).

In the process of loan optimization to maintain or improve a bank's risk-return loan portfolio balance intended to enhance consolidated bank profitability, I contend that, either through better alignment of lending policies or loan allocation redundancies of the target firm, consolidated banks may inadvertently create a credit gap in mortgage lending by supplying fewer mortgage loan originations (in number and dollar volume) and cater more toward larger loans. Thus, I propose the following.

Hypothesis 1: There will be fewer number of mortgage loans originated by the bank post-consolidation as compared to mortgage loans originated by "combined banks" pre-consolidation.

Hypothesis 2: There will be lower aggregate mortgage loan amounts originated by the bank post-consolidation as compared to aggregate mortgage loan amounts originated by "combined banks" pre-consolidation.

Hypothesis 3: There will be higher per mortgage loan amounts originated by the bank post-consolidation as compared to per mortgage loan amounts originated by "combined banks" pre-consolidation.

In the instances above, I compare the post-consolidation mortgage numbers (amounts) with the pre-consolidation values, assuming the acquirer and target were combined.

Along with the consolidating banking industry over the last 25 years, the allocation of small business lending in bank loan portfolios has also changed significantly. We observe the phenomenon in a study by the FDIC (FDIC Community Banking Study, 2012), where residential mortgage loans represented over 61% and 35% of all loans for community and noncommunity banks, respectively, in 1984 compared to 36% and 54% of all loans today. The study also reveals an increase in community banks' emphasis in real estate lending with the focus on commercial real estate loans rather than residential mortgage loans. One measure of bank loan specialization is the degree to which loans make up total assets. For example, in 1984, 29% and 13% of mortgage loans contributed to the total assets of community and noncommunity banks, respectively. However, 27 years later, the percentage of mortgage loans held by community banks decreased by 9% while noncommunity banks' percentage of mortgage loans increased by 4%. Although the FDIC community banking study separates U.S. banking organizations into either community or noncommunity, it acknowledges the difficulty of defining a community bank based on asset size alone and thus uses a multistep process in distinguishing between community or noncommunity banks. I contend the significant change that occurred in both bank consolidation and mortgage loan portfolio allocations in both community and noncommunity banks in the extant research limits potential insight into the loan specialization effect of bank consolidation on mortgage loan activity. By analyzing all bank consolidations regardless of the size of either community or noncommunity banks and the changes in mortgage loan portfolio specialization, as measured by mortgage loan growth to total assets, current FDIC data supports the declining trend in the percent of 1-4 family residential mortgages to total loans across various bank sizes. With the inclusion of 6,519 reporting institutions in 2010 compared to 4,518 in 2019 (FDIC BankFind Suite, 2022), the proportion of 1-4 family residential mortgages to total loans declined from 33% to 24% across all sizes of U.S. banks. The aforementioned Peek and Rosen (1998) study on proportions of small business lending to total asset variations pre- and post-consolidation observes a strong negative correlation between the size of a bank's total assets and its portfolio specialization of business loans. The shift toward greater loan specialization may reflect the utilization of common merger-related theories such as the efficiency and focusing hypotheses designed to increase the combined value of merging banks. Berger and Humphrey (1990) find that large bank acquirers are likely to be more efficient than their targets and thus motivated to improve the targets' efficiency to increase banks' combined value. In addition, the focusing hypothesis suggests that banks with similar focus would create more value by concentrating on a narrow area of expertise or specialization, as concluded by DeLong (2003).

I contend that as banks consolidate, thus creating a larger asset-based entity, the combined entity will behave similarly to the conclusion of the aforementioned FDIC community banking study. There will be continual decline in the proportion of mortgage loans to total loans after a consolidation. Thus, I propose the following.

Hypothesis 4: There will be a lower percent mortgage loan concentration by the bank post-consolidation as compared to the weighted average percent mortgage loan concentration originated by "combined banks" pre-consolidation.

Peek and Rosen (1998) measure the effects of small business loan growth relative to total assets for periods pre- and post-bank consolidation. The change in small business loan growth either up or down is most significant when the acquirer and target maintain different specialization in small business lending that reflects sizable impacts to the acquirer's total assets. As a result, acquiring banks tend to recast the target bank in the acquirer's image such that the small business loan portfolio converges toward the pre-consolidation loan portfolio share of the acquirer. They observe a strong negative correlation between the size of a bank's total assets and its portfolio specialization of business loans. I contend that depending on the acquiring bank's level of mortgage lending specialization, it will likely recast the target's portfolio share of mortgage loans to total assets in the acquirer's image, potentially creating an increase in the credit lending gap. The implication of this from a credit gap perspective is that if the acquiring banks maintain a lower mortgage loan allocation or specialization as compared to the target's, a decrease in mortgage originations post-consolidation will likely result, as found in the Peek and Rosen (1998) small business loan study. Thus, I propose the following.

Hypothesis 5: The post-consolidation percent mortgage loan concentration will be greater (lower) than the pre-consolidation combined bank weighted average percent mortgage loan concentration if the acquirer has a greater (lower) percent mortgage loan concentration than the target pre-consolidation.

Geographic expansion of bank assets is thought to improve cost-efficiencies and reduce risk through the economic diversity of metropolitan statistical areas (MSA) or local market risks. MSAs are defined by the Office of Management and Budget and include geographical areas that contain a core urban area of 50,000 or more inhabitants. In particular, Goetz, Laeven, and Levine (2016) find that bank holding companies that incorporate a geographical diversity leveraged MSAs with different industrial structures and business cycles lowered corporate risk while maintaining consistent loan quality as measured by increased loan loss provisions, nonperforming loans, or loan charge-offs, which are indicators of bank fragility. In contrast, research by Berger and De Young (2001) suggests that there were both positive and negative links with bank geographical scope. Banks that expand into nearby states and regions benefit from higher levels of efficiency, especially in small banks with less than $100 million in assets. In both studies, the focus was on operational efficiency and not the underlying impact to credit availability. Yet, a study by Rosen (2011) examines how lender competition affects the profile of bank loans made by using denial rate as a proxy for aggregate riskiness of loans with lower denial rates in various counties potentially indicating higher loan or borrower risk. His findings support an increasing denial rate among local banks from a rate of 12% of applicants to 19% prior to the 2008 economic crisis in comparison to other mortgage lenders, nonlocal banks (banks that do not have branches in the local market), and independent mortgage banks (IMB) that saw their denial rates drop from 40% to slightly above 25%. Stated another way, nonlocal banks and IMBs change in approval of mortgage applications increased while local banks decreased mortgage loan approvals over the same period. The caveat to the denial rates across lenders is potential differences in applicant quality and variation in the types of mortgages. While mortgage loan denial rates increased for the local banks and decreased for nonlocal banks, the denial rate for mortgage applications remains higher for nonlocal banks, suggesting that as a product of consolidation, fewer local banks may make access to mortgage loans more difficult for consumers.

Lastly, research by Jagtiani and Maingi (2018) investigating the geographic expansion of locations as a result of a bank consolidation and the effect on small business lending finds the "overall impact of community bank mergers depends significantly on where the acquirers and the targets had operations before consolidation. It supports the conventional belief that there would be an adverse impact on credit availability to the local small businesses in counties where community banks are acquired by large banks," in particular, target banks that operated outside an acquirer's county. The results indicate that small business loan activity increased in counties in which acquirers operated prior to consolidation, however offset by a decline in loan activity in counties of the target bank. Based on the aforementioned research, it appears that there is a location effect related to bank consolidation that could potentially impact the availability of loans post-consolidation. I speculate that target consolidated banks that were not located in the same city as the acquiring bank will reduce the availability of mortgage loans post-consolidation similar to the phenomenon encountered by small business loans described by Jagtiani and Maingi (2018). Thus, I propose the following.

Hypothesis 6: There will be a greater number of mortgage loan originations post-consolidation in cities where the acquirer has headquartered operations pre-consolidation, while there will be fewer mortgage loan originations in cities where the target but not the acquirer had headquartered operations pre-consolidation.

Hypothesis 7: There will be greater aggregate mortgage origination amounts post-consolidation in cities where the acquirer has headquartered operations pre-consolidation, while there will be lower aggregate mortgage origination amounts in cities where the target but not the acquirer had headquartered operations pre-consolidation.

Hypothesis 8: There will be higher per-mortgage loan amounts originated post-consolidation in cities where the acquirer has headquartered operations pre-consolidation, while there will be lower per-mortgage loan amounts in cities where the target but not the acquirer had headquartered operations pre-consolidation.

Hypothesis 9: There will be lower bank percent mortgage loan concentration post-consolidation in cities where the acquirer has headquartered operations pre-consolidation, while there will be higher bank percent mortgage loan concentration in cities where the target but not the acquirer had headquartered operations pre-consolidation.

CHAPTER IV

EMPIRICAL METHODOLOGIES AND RESEARCH DESIGN

Data Sources and Sample Selection

My data sample is extracted from three datasets: FDIC organizational structural changes, FDIC quarterly bank call reports, and HMDA data on home mortgage loan originations for the period beginning 2010 and ending 2020. The size of the three datasets varies significantly, providing for the breadth and depth of a robust event analysis. For example, over the 11-year period of study, 3,494 instances of bank consolidations occurred, while in a typical year, 6,876 banks disclose call report data associated with 6,177,475 home mortgage loans. My research on mortgage lending relies on (1-4 family) residential property data, which differs from the research of Peek and Rosengren (1998) and Jagtiani and Maingi (2018) that focus on small business lending. The use of (1-4 family) residential data, a homogeneous category of credit, helps to circumvent the problems associated with shifts in demand across different credit lending described by Dagher and Kazimov (2015).

The first dataset is extracted from the FDIC historical bank archive for the periods 2011 through 2019 that includes organizational structural changes of banks. Accordingly, the dataset excludes the periods 2010 and 2020, periods that are reflected in HMDA and

FDIC quarterly bank call report datasets as they represent one period prior to 2011 and post-2019 for each structural bank change. The structural changes reflect the creation of new institutions, business combinations (consolidations), interim mergers, reorganizations, conversions, title changes, main office relocations, and branch office openings and closings. The focus of the research is on the FDIC bank archival data specific to business combinations (consolidations). Thus, for the purpose of my study, the analysis excludes the structural data containing the creation of new institutions, interim mergers, reorganizations, conversions, title changes, main office relocations, and branch office openings and closings.

The second data source for the periods 2010 through 2020 is also from the FDIC, which provides quarterly bank call reports containing financial documentation required by regulatory bodies that includes data such as total assets, net income, total loans, number of branches, and bank locations similar to the small business lending data collected by Jagtiani and Maingi (2018).

The third data set for the periods of 2010 through 2020 pertains to mortgage loan data that is maintained by the Federal Financial Institutions Examination Council (FFIEC). The council is an interagency body that includes the Federal Reserve Board (FRB), Federal Deposit Insurance Corporation (FDIC), National Credit Union Administration (NCUA), Office of the Comptroller of the Currency (OCC), and the Consumer Financial Protection Bureau (CFPB). The FFIEC archive data are populated through the HMDA of 1975, which contains loan amounts by individual, by year, by institution, and by county. The data set includes 55 data fields; of interest to my study are the following nine data fields: As_of_year (year of mortgage origination), respondent_id (unique bank id), property_type_name (one-to-four family dwelling), property_type (code of 1 representing one-to-four family dwelling), loan_amount_000 (loan origination amount in thousands), action_take_name (loan originated), action_taken (loan originated code of 1).

The sample selection described in Table 1 was generated through several combined datasets. The quantity and dollar amount of mortgages are sourced from two HMDA datasets that contain all mortgages and entities that reported in HMDA. The larger of the two datasets, hmda_20XX_nationwide_first-lien-owner-occupied-1-4-family-records (Consumer Financial Protection Bureau, 2022)[1] averaged six million nationwide records per year. The banks that submit the nationwide records also submit a HMDA transmittal sheet dataset that reconciles to the larger, more detailed nationwide records. By joining the transmittal dataset with nationwide records by lender ID, I created a combined dataset of approximately 7,500 institution observations per year. Included in the observations were 5,700, or 77%, of observations related to mortgage data from nonbank institutions such as credit unions, financial service firms, and mortgage lenders. After reducing the dataset of nonbank institutions, approximately 1,725 bank institutions remained that needed to be merged with the FDIC structural dataset that contains bank institutions that were involved in a merger event for the periods 2011 through 2019.

The result was a dataset of 2,579 unique merger transactions including both acquirer and target bank information used as a basis for my bank consolidation and mortgage lending study. The next step in my sample selection was to combine FDIC structural data

[1] FDIC annual historical bank data from 2008 to 2019 includes commercial and industrial banks (national banks, state-chartered banks, state-charted banks that are nonmembers of the Federal Reserve System, FDIC-supervised state savings banks, OCC-supervised state savings banks, federal and state savings and loans). The dataset excludes non-FDIC insured commercial banks, thrifts, and credit unions.

with the HMDA bank mortgage data. Unfortunately, a common lender ID or respondent ID were not consistently used. To combine the data, I joined the two datasets on criteria such as lender ID; respondent ID; respondent name, date, mailing address, respondent city, zip code, or state. The derived combined dataset was reduced by 1,017 observations of unmatched HMDA and FDIC structural data. Since there is not a common bank ID across the data sets, the likelihood of excluding an observation due to misspellings or data input errors are present. Further, since HMDA and FDIC banks have different regulatory reporting requirements, it is not uncommon for FDIC structural data institutions to not report HMDA data.

Table 1. Sample Selection Description and Composition

Sample Details	**Number of Observations**
FDIC bank combinations for periods 1-1-2011 through 12-31-2019	2,579
Reduced by unmatched HMDA and FDIC bank combinations	(1,017)
FDIC bank combinations matched with HMDA data	1,562
Reduced by target bank elimination post-event	(613)
Pre-and post-event banks	949
Reduced by combination of target and acquirer pre-consolidation	(589)
Pre- and post-banks in the final sample	361

The 1,562 remaining matched HMDA and FDIC structural observations consisting of 781 acquirer banks and 781 target banks were joined on lender ID and date with FDIC quarterly call report bank financial data. The result was a dataset with observations that included bank institution, number of mortgage originations, mortgage amounts, total loans, net income, and total assets for the period of 2010 through 2020. Finally, in the process of establishing a bank consolidation event window of one year prior and one year post, a natural reduction of 613 consolidated target banks occurs, with only the acquiring bank remaining post-consolidation. Also, a natural reduction of 589 observations occurs due to the combination of target and acquirer banks to establish a pre-consolidation combined data point. Thus, the combination of the three datasets provides a robust sample size of 361 public data observations to test the relationships between bank consolidations and mortgage originations.

The sample selection is further described by year in Table 2 for the mergers in 2011 through 2019, with the smallest percent of samples occurring in 2011 and 2012. Otherwise, the sample distribution is comparable from 2013 through 2019.

I established the sample selection for nonconsolidated banks by joining HMDA data with FDIC quarterly call reports, which resulted in a sample size of 26,568 observations for the periods 2010 through 2020. To best establish a control group of nonconsolidated banks and consistent with Mallin, Saadouni, and Briston (1995), I applied a matched pairs design. Further, I based the match pairs design on the amount of mortgage loans originated by year for each nonconsolidated bank within a plus or minus 5% amount variation criteria window. The result was a match pair of control firms for each consolidated treatment firm of 361 sample observations or a combined sample set of treatment and control firms of 722.

Table 2. Merger Events by Year Included in the Sample

Years	Mergers	Percent of Sample
Ending December 31, 2011	5	1
Ending December 31, 2012	28	8
Ending December 31, 2013	54	15
Ending December 31, 2014	45	12
Ending December 31, 2015	46	13
Ending December 31, 2016	53	15
Ending December 31, 2017	42	12
Ending December 31, 2018	48	13
Ending December 31, 2019	40	11
Total	361	100

Empirical Design

To test each of the hypotheses, I use a time fixed effects event regression framework with the dependent variable expressed as the change in the variable of interest from the post-consolidation calendar year $t + 1$ to pre-consolidation calendar year $t - 1$. The regression is estimated over all consolidated and nonconsolidated banks of matched pairs sample observations. Further, the combined sample set of 722 treatment and control firms excludes consolidating banks if they were involved in another consolidation in years $t - 3$ to $t - 1$ or subsequently in years $t + 1$ to $t + 3$ where t is the calendar year of consolidation. A similar restriction is imposed on nonconsolidating banks. These restrictions are imposed to ensure that the effects being measured are for the consolidation event in question.

For the first four hypotheses, I used the same basic regression model though the dependent variables are different. The dependent variable is regressed on an indicator variable indicating whether the bank was subject to consolidation and several control variables. Thus, regression model (1) is designed to estimate the change in quantity, amount, per-loan amount, and percent of mortgage concentration subject to bank consolidation.

$$\begin{aligned}\Delta y_{i,(t+1)-(t-1)} = {} & \beta 0 + \beta 1\ \mathit{Consolidated}_{i,t} + \beta 2\ \mathit{Profit}_{i,t-1} + \beta 3\ \mathit{BankSize}_{i,\ t-1} \\ & + \beta 4\ \mathit{30\text{-}year\ fixed\ rates}_{i,\ t-1} + \mathit{Calendar\ year\ fixed\ effect} + \varepsilon_{i,t}\end{aligned} \tag{1}$$

$\Delta y_{i,(t+1)-(t-1)}$ is the dependent variable of interest and varies with the hypothesis. It is the change in the variable of interest. For example, in Hypothesis 1 it is the quantity of mortgage loans in the post-consolidation calendar year ($t + 1$) minus the corresponding quantity of mortgage loans originated in the pre-consolidation calendar year ($t - 1$) on a “combined” basis. Banks that did not consolidate are part of the matched pairs design and serve as control firms. The *Consolidated*$_i$ independent variable is defined as an indicator variable coded as 1 for “yes” and 0 for “no” in the event a bank consolidation occurred in year *t*. In line with the Jagtiani and Maingi (2018) research, my regression models include control variables: $Profit_{it-1}$, bank profitability measured by net income/total assets, and $BankSize_{it-1}$ measured by total assets, both measured as of $t-1$. In addition, to control for variability of economic factors over the period of study, I include both *30-year fixed rates* from 2010 through 2020 and *Calendar year fixed effect* variables to control for any time trend changes in the dependent variable.

As noted, the dependent variable differs depending on the hypothesis being tested.

For Hypothesis 1, the dependent variable *QTY* (quantity of mortgage loan originations) is as follows:

$\Delta y_{n,i,\ (t+1)-(t-1)} = (y_{n\,t+1} - y_{n\,t-1})_i$ = the change in the quantity of home mortgage loans originated post-consolidation $y_{n_{t+1}}$ period less the quantity of home mortgage loans at origination pre-consolidation $y_{n_{t-1}}$ by $bank_i$ where y_n equals the quantity of home mortgage loans.

For Hypothesis 2, the dependent variable, *AMT* (dollar amount of mortgage loan originations) is as follows:

$\Delta y_{a,i,\ (t+1)-(t-1)} = (y_{a\,t+1} - y_{a\,t-1})_i$ = the change in the aggregate home mortgage loan amount at origination post-consolidation period $y_{a_{t+1}}$ less the aggregate home mortgage loan amount preconsolidation period $y_{a_{t-1}}$ by $bank_i$ where y_a equals mortgage loan amount.

For Hypothesis 3, the dependent variable, *PLA* (per-loan amount) is as follows:

$\Delta y_{a/n,i,\,(t+1)\,-\,(t-1)} = ((y_{a\,t+1} / y_{n\,t+1}) - (y_{a\,t-1} / y_{n\,t-1}))_i$ = the change in the per mortgage loan amount at origination post-consolidation period less the per mortgage loan amount at origination pre-consolidation where y_a equals mortgage loan amount and y_n equals the quantity of home mortgage loans.

For Hypothesis 4, the dependent variable, *PMF* (percent mortgage focus) is as follows:

$\Delta y_{\%i} = ((y_{aml\,t+1} / y_{atl\,t+1}) -$ Weighted Average $(y_{caml\,t-1} / y_{catl\,t-1}))_i$ describes the change in percent of the proportion of mortgage loans (y_{aml}) to total loans (y_{atl}) post-consolidation period less the weighted average of the combined proportion of mortgage loans (y_{caml}) to combined total loans (y_{catl}) pre-consolidation.

For Hypothesis 5, the dependent variable *PMF* is the same as with Hypothesis 4; however, the objective is to determine whether the acquiring firm's loan specialization pre-consolidation influences the surviving firm's percent of mortgage focus post-consolidation when applied solely to the Treatment group, a subset of sample observations subject to a bank consolidating event. To test Hypothesis 5, I estimate the following regression Equation (2), which is similar to Equation (1) with the exception of a different indicator variable *Specialized.* Where *Specialized* is an indicator variable that is coded 1 or "Yes" if the ratio of mortgage loans to total loans pre-consolidation is greater for the acquiring bank compared to the ratio of the target bank, otherwise the indicator variable indicates 0 or "No". Regression Equation (2) is designed to test the sensitivity of the change in percent of mortgage concentration around consolidation events to the acquirer's loan specialization pre-consolidation.

$$\Delta y_{\% i\ (t+1)-(t-1)} = \beta 0 + \beta 1\ Specialized_{i\ t-1} + \beta 2\ Profit_{i\ t-1} + \beta 3\ BankSize_{i\ t-1} + \beta 4\ 30\text{-}year\ fixed\ rates_{i\ t-1} + Calendar\ year\ fixed\ effect + \varepsilon_{i\ t} \tag{2}$$

For Hypotheses 6 through 9, the dependent variables are consistent with dependent variables applied in Hypotheses 1 through 4. However, the objective of Hypotheses 6 through 9 is to determine whether the location of an acquirer and target's operational headquarters affects the credit supply of mortgage loans post-consolidation based on the sample observations of the Treatment group alone. Thus, regression model (3) is applied to Hypotheses 6 through 9 but will differ in the use of the aforementioned four dependent variables in addition to an indicator variable of *Location.* If the target and acquiring banks have headquartered operations in the same city prior to consolidation, 1 indicates "yes" and 0 indicates "no". Regression Equation (3) is designed to estimate the sensitivity of change in the quantity of mortgage loans, amount of mortgage loans, per-mortgage loan amount, and percent of mortgage loan concentration around consolidation events to the relative location of the consolidating banks, i.e., whether their pre-consolidation headquarters are in the same or different cities.

$$\Delta y_{i,(t+1)-(t-1)} = \beta 0 + \beta 1\ Location_{it-1} + \beta 2\ Profit_{it-1} + \beta 3\ BankSize_{it-1} + \beta 4\ 30\text{-}year\ fixed\ rates_{it-1} + Calendar\ year\ fixed\ effect + \varepsilon_{it} \tag{3}$$

CHAPTER V

RESULTS AND DISCUSSION

Descriptive Statistics

The descriptive statistics for the dataset are presented in Table 3. Panel A describes data for the combined set of treatment and control firms, while Panels B and C describes data separately for each. Within each panel, variables are classified as dependent variables, control variables, and independent variables. The dependent variables include: *QTY* (quantity of mortgage loan originations), *AMT* (dollar amount of mortgage loan originations), *PLA* (per-loan amount), and *PMF* (percent mortgage focus). Summary statistics for the dependent variables are shown for both temporal periods, pre-consolidation and post-consolidation.

Panel A shows the mean (median) *QTY* is 1,197 (329) in the pre-consolidation period, considerably larger at 1,711 (346), representing an increase of 43% (5%) in the mean (median) in the post-consolidation period. The mean (median) *AMT* is $276,579,472 ($66,138,000) in the pre-consolidation period, considerably larger at $404,890,082 ($69,292,000), an increase of 46% and (5%) in the mean (median) in the post-consolidation period. The mean (median) *PLA* is $360,412 ($283,770) in the pre-consolidation period and somewhat smaller at $294,775 ($217,231), a decrease of 18% and (23%) in the mean (median) in the post-consolidation period. The mean (median) *PMF* is 0.2853 (0.2244) in the pre-consolidation period, while it is somewhat larger at 0.3436 (0.2972), reflecting an increase of 20% and (32%) in the post-consolidation period. Whether these patterns hold for treatment or control firms, or both will become evident from Panels B and C, which present the summary statistics separately for these two samples.

Panel A also reveals that there is considerable variation between the mean and median for the control variable, *BankSize* with a mean (median) of $3,044,439,774 ($687,559,200) or a 4.4 times magnitude difference. The *Profit* and *30-Year Fixed Rates* control variables have a mean (median) of 0.0097 (0.0091) and 0.0399 (0.0398), respectively.

Table 3 Panel A concludes with the statistics on the indicator independent variables: *Consolidated, Specialized*, and *Location* within the sample observations. As expected, the indicator variable *Consolidated* describes a value of 1 for 50% of the total sample of 722 firms, consistent with the fact that the total sample is evenly split between 361 banks in the Treatment Group that were subject to consolidation and a match sample of 361 Control Banks that did not experience a consolidation. The *Specialized* and *Location* variables are applied to a subset, or the Treatment Group of banks, subject to a consolidation event. The 41%, or 148, of the *Specialized* variable observations refer to the acquiring banks that had a greater mortgage loan focus relative to target banks. The 20%, or 73, of the *Location* variable observations refers to banks subject to bank consolidation that maintained headquartered locations in the same city pre-consolidation.

Table 3 also describes descriptive statistics in Panel B for Treatment Group variables, and Panel C for Control Group variables. The dependent variables include: *QTY, AMT, PLA,* and *PMF* similar to Panel A. Summary statistics for the Treatment Group dependent variables shown in Panel B for both temporal periods, pre-consolidation and post-consolidation are as follows: The mean (median) *QTY* is 1,146 (352) in the pre-consolidation period, while the post-consolidation *QTY* is 1,621 (350), representing a considerable increase of 41% for the mean but a 1% decrease for the median. The mean (median) *AMT* is $274,752,097 ($66,104,000) in the pre-consolidation period and considerably larger at $374,338,166 ($65,344,000) in the post-consolidation period, an increase of 36% and a decrease of 1%, respectively. The mean (median) *PLA* is $461,444 ($377,357) in the pre-consolidation period, while considerably smaller in the post-consolidation period at $294,901 ($224,889), a decrease of 36% and 40% in the mean and median, respectively. The mean (median) *PMF* is 0.1688 (0.1507) in the pre-consolidation period, and much larger in the post-consolidation period at 0.3003 (0.2730), an increase of 78% and 81%, respectively.

Lastly, Table 3 Panel C describes the same dependent variables as Panel B, but the summary statistics are for the Control Group sample observations. The mean (median) *QTY* is 1,248 (320) in the pre-consolidation period, while considerably larger in the post-consolidation period at 1,800 (346) or an increase of 44% and 8%, respectively. The mean (median) *AMT* is $278,406,847 ($66,172,000) in the pre-consolidation period, and considerably larger in the post-consolidation period at $435,441,997 ($75,325,000), or an increase of 56% and 14%, respectively. The mean (median) *PLA* is $259,379 ($189,604) in the pre-consolidation period, and slightly greater in the post-consolidation period at $294,651 ($206,305) or an increase of 14% and 9%, respectively. The mean (median) *PMF* is 0.4019 (0.3538) in the pre-consolidation period, while it is slightly smaller in the post-consolidation period at 0.3870 (0.3416) or a decrease of 4% and 3%, respectively.

The patterns of either increasing or decreasing change for pre- and post-consolidation are consistent for the Panel A combined sample observations, with the magnitude of change more apparent in the mean summary statistic as compared to the median. The Panel B Treatment Group summary statistics were consistent with Panel A summary statistics except the median change from pre- to post-consolidation. The median change in *QTY* and *AMT* from pre- to post-consolidation is slightly declining or flat in the Treatment Group, whereas Panel A combined median change from pre- to post-consolidation increased for dependent variables *QTY* and *AMT.* Also interesting is the magnitude of change of the dependent variables *PLA* and *PMF* pre-and post-consolidation observed in Panel B Treatment Group summary statistics as compared to Panel A. The Panel B Treatment Group's respective *PLA* and *PMF* mean (median) change of 36% (40%) and 78% (81%) is considerably higher than Panel A combined mean (median) change of 18% (23%) and 20% (32%). A preliminary inference drawn from Table 3 Panels A and B is that there appears to be a relationship between the magnitude and directional change of the Treatment Group relative to the assertions of Hypotheses 1 through 4.

The patterns of the Panel C Control Group summary statistics are mixed relative to both the Panel A combined summary statistics and the Panel B Treatment summary statistics. The Panel C Control Group summary statistics differ directionally and in magnitude with the Panel A combined statistics as *PLA* increases and the *PMF* decreases for both mean and median pre- to post-consolidation. Further, the Panel C Control Group median summary statistic differs directionally and in magnitude of change as compared to the Panel B Treatment median for all dependent variables pre- to post-consolidation.

The pattern suggests that perhaps the Panel B Treatment Group pre- to post-consolidation change is experiencing a consolidation phenomenon on its dependent variables as previously hypothesized, and thus is subject to further discussion through univariate analysis.

Table 3. Descriptive Statistics

Panel A. Continuous Variables

Variable Name		*N*	Mean	Median	Std Dev	Min	Max
Dependent Variables							
QTY	Pre	722	1,197	329	3,793	1	70,860
	Post	722	1,711	346	6,201	2	113,043
AMT	Pre	722	276,579,472	66,138,000	745,119,064	534,000	9,102,289,000
	Post	722	404,890,082	69,292,000	1,159,603,171	240,000	14,024,627,000
PLA	Pre	722	360,412	283,770	315,537	47,854	4,533,661
	Post	722	294,775	217,231	370,134	31,434	633,693
PMF	Pre	722	0.2853	0.2244	0.2091	0.0084	0.9990
	Post	722	0.3436	0.2972	0.3436	0.0075	0.9991
Control Variables							
Profit		722	0.0097	0.0091	0.0060	(0.0222)	0.0570
BankSize		722	3,044,439,774	687,559,200	9,943,905,168	38,692,800	126,193,200,000
30-Year Fixed		722	0.0399	0.0398	0.0028	0.0365	0.0454

Discrete Variables

Variable Name	*N*	Number	Percent
Independent Variables			
Consolidated	722	361	50.0
Specialization	361	148	41.0
Location	361	73	20.2

Panel B. Continuous Variables (Treatment)

Variable Name		*N*	Mean	Median	Std Dev	Min	Max
QTY	Pre	361	1,146	352	2,551	3	20,443
	Post	361	1,621	350	4,334	2	44,181
AMT	Pre	361	274,752,097	66,104,000	724,360,966	548,000	7,977,640,000
	Post	361	378,968,892	65,646,000	1,037,304,087	240,000	9,295,085,000
PLA	Pre	361	461,444	377,357	360,244	94,230	2,216,236
	Post	361	294,901	224,890	232,500	66,966	633,693
PMF	Pre	361	0.1668	0.1507	0.0849	0.0222	0.4817
	Post	361	0.3003	0.2730	0.1637	0.0075	0.9184

Panel C. Continuous Variables (Control)

Variable Name		*N*	Mean	Median	Std Dev	Min	Max
QTY	Pre	361	1,248	320	4,723	1	70,860
	Post	361	1,800	346	7,630	3	113,043
AMT	Pre	361	278,406,847	66,172,000	766,316,880	534,000	9,102,289,000
	Post	361	435,441,997	75,325,000	1,270,914,022	555,000	14,024,627,000
PLA	Pre	361	259,379	189,604	221,712	47,854	1,779,350
	Post	361	294,651	206,306	469,386	31,434	633,693
PMF	Pre	361	0.4019	0.3537	0.2307	0.0084	0.9991
	Post	361	0.3870	0.3416	0.2276	0.0091	0.9992

See Appendix for the variable definitions.

Univariate Analysis

To better understand the potential consolidation phenomenon, a univariate analysis is provided in Table 4. Table 4 Panel A shows the mean and median changes in the test variables for Hypotheses 1 through 4 and their significance levels for the Treatment and Control Groups separately. Rather than focus exclusively on parametric test such as the student's *t*-test of independent means, I also incorporate nonparametric tests of Sign Test and Wilcoxon Signed Rank Test consistent with Sinha, Kaushik, and Chaudhary (2010). By analyzing the Treatment and Control Groups separately, I identify significant differences in pre- and post-event sample observations.

In Table 4 Panel A, I observe that the mean and median *QTY* values were greater after consolidation for both the Treatment and Control Groups. I also find the mean and median differences of both Treatment and Control *QTY* variables are significant at the 1% level; however, the Sign Test alone does not support a significant median difference at the 10% level. The Treatment Group mean *AMT* values were greater and the median *AMT* values were slightly lower compared with greater mean and median values for the Control Group after consolidation. The mean and median differences of both the Treatment and Control *AMT* variables are significant at the 1% level across all tests. The Treatment Group mean, and median *PLA* values decreased compared with an increase in mean and median values for the Control Group after consolidation. The *PLA* variable differences of means and medians are significant at the 1% level across all tests. Lastly, the Treatment Group mean and median *PMF* values increased compared with a decrease in mean and median values for the Control Group after consolidation. The *PMF* variable differences of means and medians are significant at the 1% level across all tests within both Treatment and Control sample observations.

Of note, *QTY* and *AMT* variable values in both Treatment and Control Groups were consistent in directional change but inconsistent with my stated Hypotheses 1 and 2. In contrast, *PLA* and *PMF* variable values' directional change did not align in between Treatment and Control Groups. Specifically, I observed a decline in per-loan amounts post-consolidation, opposite to my expectation outlined in Hypothesis 3. In contrast, the Control Group's mean and median per-loan amounts increased post-consolidation. My observation of the *PMF* variable change was also inconsistent with my Hypothesis 4 assumptions of lower percent mortgage focus post-consolidation, while for the results the Control Group were opposite.

Table 4 univariate analysis Panel B includes a difference-in-difference (DID) analysis similar to research of Argarwal and colleagues (2015) used to help determine preliminary statistical inference between Treatment and Control Groups. The results of the DID analysis show that the differences in means and medians of *QTY* and *AMT* variables are not significant across all measurement tests at the 10% level. This suggests that dependent *QTY* and *AMT* variables are not likely subject to the influences of the bank consolidation sample observations under univariate assumptions. In contrast, both dependent *PLA* and *PMF* variable mean and median differences are significant at the 1% level across all measurement tests. While statistically significant, the results are contrary to my expectations in Hypotheses 3 and 4. Although still preliminary and pending further rigorous regression estimates, the potential importance of the univariate analysis results of H3 and H4 suggests that a causal relationship may exist between bank consolidation and the per-loan amount and percent mortgage focus in the sample observations.

Table 4. Univariate Analysis of Hypotheses 1 through 4

Panel A. H1 – H4 Univariate Analysis of Treatment and Control Groups Separately

		Pre-Event	Post-Event	Mean Difference	*t*-test Statistic	Pre-Event	Post-Event	Median Difference	Sign Test Statistic	Wilcoxon Signed Rank Test Statistic
QTY	H1(T)	1,146	1,621	474	3.3200***	352	350	(2)	8.00	6,242.50***
	H1(C)	1,248	1,800	552	2.9758***	320	346	26	6.00	6,242.50***
AMT	H2(T)	274,752,097	378,968,892	104,216,795	3.1021***	66,104,000	65,646,000	(458,000)	29.50***	8,375.50***
	H2(C)	278,406,848	435,441,997	157,035,149	4.4885***	66,172,000	75,325,000	9,153,000	36.50***	10,986.50***
PLA	H3(T)	461,444	294,901	(166,543)	-12.5604***	377,358	224,890	(152,468)	-123.50***	-23,915.00***
	H3(C)	259,379	294,651	35,271	1.7262***	189,605	206,306	16,701	58.50***	11,095.50***
PMF	H4(T)	0.1688	0.3003	0.1315	27.6693***	0.1507	0.2730	0.1233	168.50***	32,130.50***
	H4(C)	0.4019	0.3870	(0.0149)	-5.2279***	0.3537	0.3416	(0.0121)	-48.50	-11,173.00***

Panel B. H1 – H4 Difference-in-Difference Analysis of Treatment and Control Groups

		Control	Treatment	Mean Difference	*t*-test Statistic	Control	Treatment	Median Difference	Sign Test Statistic	Wilcoxon Signed Rank Test Statistic
QTY	H1	552	474	(77)	-0.3724	26	(2)	(28)	5.50	-302.00
AMT	H2	157,035,149	104,216,795	(52,818,354)	-1.2729	9,153,000	(458,000)	(9,611,000)	-3.50	-2,032.50
PLA	H3	35,271	(166,543)	(201,814)	-8.8605***	16,701	(152,468)	(169,169)	-120.50***	-26,242.00***
PMF	H4	(0.0149)	0.1315	0.1464	25.8214***	(0.0121)	0.1223	0.1344	162.50***	31,530.50***

N = 361. N.B. ***, **, and * indicate that the coefficient estimates are different from zero at the .01, .05, and .10 probability levels, respectively, for a two-tailed test.

Table 5 presents a univariate analysis of Hypothesis 5. As H5 predicts that acquirers' specialization in mortgage lending will be recast on the remaining post-consolidation entity, the Treatment Group is classified into two subsamples. *Specialized* is the first group of observations defined as acquiring firms that exceed the ratio of mortgage lending to total lending relative to their target firms' ratios of mortgage lending to total lending. The second group of observations is classified as *Nonspecialized*, defined as acquiring firms that do not exceed the ratio of mortgage lending to total lending compared to their target firms' ratios. I observe that the mean and median values are greater after consolidation for both the *Specialized* and *Nonspecialized* groups. I also find the mean and median differences are significant at the 1% level across all measurement tests. However, when applying the univariate analysis, the mean and median differences are not significant at the 10% level across all measurement tests. The univariate analysis suggests that there does not appear to be an effect of acquirers recasting the percent mortgage focus in their image post-consolidation, as asserted in Hypothesis 5.

Table 5. Univariate Analysis of Hypothesis 5

Panel A: H5 Univariate Analysis of Treatment and Control Groups Separately

	N	**Group**	**Pre-Event**	**Post-Event**	**Mean Difference**	***t*-test Statistic**	**Pre-Event**	**Post-Event**	**Median Difference**	**Sign Test Statistic**	**Wilcoxon Signed Rank Test Statistic**
PMF	361	Treatment	0.1688	0.3000	0.1312	27.6693***	0.1507	0.2730	0.1223	168.50***	32,130.50***
	361	Control	0.4018	0.3870	(0.0148)	(5.2279)***	0.3537	0.3416	(0.0121)	-48.50***	-11,173.00***

Panel B: H5 Difference in Difference Analysis of Treatment and Control Groups

	N		**Control**	**Treatment**	**Mean Difference**	***t*-test Statistic**	**Control**	**Treatment**	**Median Difference**	**Sign Test Statistic**	**Wilcoxon Signed Rank Test Statistic**
PMF	361		(0.0148)	0.1312	0.1460	26.4325***	(0.0121)	0.1223	0.1344	162.5000***	-31,547.50***

Panel C: H5 Univariate Analysis of Treatment Group Between Acquiring Bank's Mortgage Specialization and Nonspecialization

	N	**Group**	**Pre-Event**	**Post-Event**	**Mean Difference**	***t*-test Statistic**	**Pre-Event**	**Post-Event**	**Median Difference**	**Sign Test Statistic**	**Wilcoxon Signed Rank Test Statistic**
PMF/Acquirer	148	Specialized	0.1619	0.2817	0.1198	17.3052***	0.1444	0.2661	0.1217	-68.00***	-5,376.00***
	213	Nonspecialized	0.1736	0.3131	0.1395	21.7642***	0.1539	0.2833	0.1294	-100.50***	-11,257.50***
PMF/Acquirer Difference	361	Specialized/ Nonspecialized			(0.0197)	27.6694***			(0.0077)	0.8651	32,130.50***

N.B. ***, **, and * indicate that the coefficient estimates are different from zero at the .01, .05, and .10 probability levels, respectively, for a two-tailed test.

Table 6 Panel A univariate analysis of Hypotheses 6 through 9 test the differences within the Treatment Group subject to the potential proximity effects when an acquiring bank's headquartered location is the *Same* or *Different* as the target bank's headquartered location. The objective of Hypotheses 6 through 9 is to build upon Hypotheses 1 through 4 dependent variables described above, but with the moderation of proximity effects to evaluate any potential relationship between dependent variables: *QTY, AMT, PLA*, and *PMF* with the *Same* or *Different* headquartered locations of both the acquirer and target.

Table 6 Panel A describes the mean and median difference for *QTY, AMT, PLA*, and *PMF*. I observe that the mean *QTY* values increase after consolidation for both *Same* and *Different* location groups. However, median *QTY* values decreased for both *Same* and *Different* location groups after consolidation. Additionally, the mean and median differences of both location groups are not significant at the 10% level across all measurement tests. The mean *AMT* values increased in both location groups post-consolidation; however, the median *AMT* values decreased in both location groups post-consolidation. The measurement tests indicate that the mean and median differences for both location groups are not significant at the 10% level. The mean and median *PLA* values decline for both location groups after consolidation and are significant across all measurement tests at the 1% level. Lastly, I observe an increase in *PMF* mean and median values for both location groups after consolidation. Additionally, the mean and median differences are significant at the 1% level for all measurement tests and both location groups after consolidation. Of note, *QTY* and *AMT* variable mean value directional differences in the *Same* and *Different* location groups are consistent; however, the median differences decrease post-consolidation rather than increase as anticipated by the assumptions of Hypotheses 6 and 7. In contrast, *PLA* and *PMF* variable mean and median values differences are consistent directionally with both *Same* and *Different* location groups. Accordingly, I observe a decline in the per-loan amounts post-consolidation in both *Same* and *Different* location groups, opposite to my assumptions in Hypothesis 8. I also observe an increase of percent mortgage focus in both *Same* and *Different* location groups, opposite to my assumptions in Hypothesis 9.

Table 6 Panel B highlights an analysis of mean and median differences within *Same* and *Different* locations across my study's dependent variables *QTY, AMT, PLA*, and *PMF* to evaluate potential influences a location moderator may have on sample observations. I find no apparent effect of location moderation across the statistical measurement tests, and thus doubt headquartered proximity of acquirer to target bank results in either lower mortgage loan originations, amounts, percent mortgage focus, or higher per-loan amounts post-consolidation.

Table 6. Univariate Analysis of Hypotheses 6 through 9 for Same and Different Bank Event Locations

Panel A: H6 – H9 Univariate Analysis of Same and Different Bank Event Locations Within Treatment Group

		N	Group	Pre-Event	Post-Event	Mean Difference	*t*-test *p*-value	Pre-Event	Post-Event	Median Difference	Sign Test *p*-value	Wilcoxon Signed Rank Test *p*-value
QTY	H6	73	Same Location	740	1,145	405	0.3310	231	175	(56)	0.6207	0.6725
	H6	288	Different Location	1,249	1,741	492	0.1182	422	398	(25)	0.5054	0.8307
AMT	H7	73	Same Location	201,087,192	300,324,137	99,236,945	0.3856	41,601,000	32,745,000	(8,856,000)	0.4095	0.7542
	H7	288	Different Location	293,424,104	398,903,153	105,479,049	0.1814	76,271,000	75,737,000	(534,000)	0.8677	0.6577
PLA	H8	73	Same Location	549,420	368,536	(180,884)	0.0207**	392,855	262,641	(130,214)	0.0005***	0.0001***
	H8	288	Different Location	439,144	276,236	(162,908)	0.0001***	375,053	221,814	(153,239)	0.0001***	0.0001***
PMF	H9	73	Same Location	0.1698	0.2990	0.1291	0.0001***	0.1468	0.2724	0.1256	0.0001***	0.0001***
	H9	288	Different Location	0.1685	0.3006	0.1320	0.0001***	0.1513	0.2738	0.1225	0.0001***	0.0001***

Panel B: H6 – H9 Mean and Median Analysis of Same and Different Event Locations

		Group	Mean Difference	*t*-test *p*-value	Median Difference	Sign Test *p*-value	Wilcoxon Signed Rank Test *p*-value
QTY	H6	Same/Different Location	(87)	0.7439	(32)	0.1560	0.9765
AMT	H7	Same/Different Location	(6,242,103)	0.9331	(8,322,000)	0.1577	0.3935
PLA	H8	Same/Different Location	(17,977)	0.6897	23,025	0.4960	0.6089
PMF	H9	Same/Different Location	-0.0029	0.7977	0.0030	0.5301	0.7973

N.B. ***, **, and * indicate that the coefficient estimates are different from zero at the .01, .05, and .10 probability levels, respectively, for a two-tailed test.

Model Results

The model results included in Tables 7 through 9 utilize ordinary least squares time fixed effects panel regressions. Table 7 describes both full and reduced form regression estimates for Hypotheses 1 through 4. The key independent variable of interest is *Consolidated* and its effect on dependent variables *QTY, AMT, PLA*, and *PMF*. The regression model estimate (1) results in Table 7 describe the effects of the listed independent variables on the dependent variable *QTY* for Hypothesis 1, in brief, states that there will be fewer number of mortgage loans originated post-consolidation as compared to pre-consolidation. The full regression model estimate (1) generates an F-statistic of 17.86, with significance at the 1% level and an adjusted R^2 of 20%. The reduced form model and key individual coefficient for the independent variable *Consolidated* are not significant at the 10% level. Although the full regression model estimate does not support Hypothesis 1, the coefficient for *Consolidated* is consistent in its direction of fewer mortgage loan originations post-consolidation relative to pre-consolidation.

The next regression model estimate (2) results in Table 7 describe the effects of the listed independent variables on the dependent variable *AMT* for Hypothesis 2, which in brief states that there will be lower aggregate mortgage loan amounts post-consolidation as compared to pre-consolidation. The full regression model estimate yields an F-statistic of 16.13 and significance at the 1% level, with an adjusted R^2 of 19%. The reduced form model and key individual coefficient for independent variable *Consolidated* are not significant at the 10% level but are directionally correct in estimation of lower aggregate mortgage loan amounts post-consolidation relative to pre-consolidation. However, the full regression model estimate does not support Hypothesis 2.

Regression model estimate (3), described in Table 7, reflects the listed independent variables and their effect on dependent variable *PLA* for Hypothesis 3, which states briefly that higher per-mortgage loan amounts will be originated pre-consolidation as compared to post-consolidation. The full regression and reduced form model estimates generate F-statistics of 7.59 and 68.65, respectively, and both are significant at the 1% level, with an adjusted R^2 of 9%. The key individual coefficient for independent variable *Consolidated* is also significant at the 1% level, with a coefficient estimate of -201.18, the opposite of my predicted direction. Therefore, the full regression and reduced form model estimates do not support Hypothesis 3.

Regression model estimate (4), described in Table 7, reflects the listed independent variables and their effect on dependent variable *PMF* for Hypothesis 4, which states briefly that there will be lower percent mortgage loan concentration post-consolidation as compared to the weighted average percent mortgage loan concentration pre-consolidation. The full regression and reduced form model estimates yield F-statistics of 64.86 and 698.68, respectively, and significance for both is at the 1% level, with an adjusted R^2 of 49%. The key individual coefficient for independent variable *Consolidated* is significant at the 1% level with a coefficient estimate of 15%, the opposite of my predicted direction. Accordingly, neither full regression nor reduced form model estimates support Hypothesis 4.

Table 7. Regression Results for Hypotheses 1 through 4 Regression of Independent Bank Consolidation Variable on the Change on Dependent Variables *QTY*, *AMT* (in Millions), *PLA* (in Thousands), *PMF*, *RFM*, and *FRM*

	***RFM* (1)**	***FRM* (1)**	***RFM* (2)**	***FRM* (2)**	***RFM* (3)**	***FRM* (3)**	***RFM* (4)**	***FRM* (4)**
Variable	*QTY*	*QTY*	*AMT*	*AMT*	*PLA*	*PLA*	*PMF*	*PMF*
Consolidated	-78.59	-20.64	-52.82	-41.55	-201.81***	-201.18***	0.15***	0.15***
	(233.95)	(208.66)	(47.91)	(43.22)	(24.36)	(24.30)	(0.01)	(0.01)
Profit		25,779.31		5,894.03		-1,150.27		0.07
		(17,765.88)		(3,679.77)		(2,069.01)		(0.47)
30-Year Fixed		11,000.84		4.06**		2,278.71**		-0.85
		(9,899.25)		(2.05)		(1,152.86)		(0.26)
BankSize		1.27***		0.00***		0.00***		9.51
		(1.05)		(0.00)		(0.00)		(2.79)
2011		-812.97		-201.29		9.97		0.04
		(963.16)		(195.85)		(112.17)		(0.03)
2012		-757.90		-191.88		-58.03		0.03***
		(472.95)		(101.09)		(55.08)		(0.01)
2013		-1,324.75***		-313.13***		-72.63		0.02*
		(420.54)		(86.55)		(48.98)		(0.01)
2014		-1,156.14***		-243.01***		-92.74*		0.02*
		(446.36)		(89.44)		(51.98)		(0.01)
2015		-847.31**		-181.22***		-62.29		0.02
		(423.24)		(88.76)		(49.29)		(0.01)
2016		-842.65**		-224.84***		-53.81		0.00
		(399.02)		(86.42)		(46.47)		(0.01)
2017		313.27		17.56		-87.33*		0.02**
		(442.72)		(91.06)		(51.56)		(0.01)
2018		428.15		73.50		-3.72		0.03**
		(462.96)		(87.91)		(53.92)		(0.01)
Intercept	551.99***	433.43	157.04***	159.95**	35.27**	89.78	-0.01***	-0.03***
	(165.43)	(390.03)	(33.88)	(80.79)	(17.22)	(45.42)	(0.00)	(0.01)
Model Statistics								
Adjusted R^2 (%)	0.00	0.20	0.00	0.19	0.09	0.09	0.49	0.49
F-Statistic	0.11	17.86***	1.22	16.13***	68.65***	7.59***	698.68***	64.86***

N = 422. The coefficients are the top row; the robust standard errors are shown in parenthesis. ***, **, and * indicate that the coefficient estimates are different from zero at the .01, .05, and .10 probability levels, respectively, for a two-tailed test.

The regression model estimate (5) results described in Table 8 reflect the listed independent variables and their effect on dependent variable *PMF* for Hypothesis 5, which states briefly that post-consolidation percent mortgage concentration will be greater than the pre-consolidation combined bank weighted average percent mortgage loan concentration if acquirers have a greater percent mortgage loan concentration than targets pre-consolidation. The full and reduced form regression model estimates generate F-statistics of .77 and .46, respectively, and are not significant at the 10% level, with a corresponding adjusted R^2 of 0%. Furthermore, the key individual coefficient for independent variable *Specialization* is not significant at the 10% level, with a coefficient estimate of -1%, the opposite of my predicted direction. I find no significant relationship between acquirer banks' specialization of mortgage lending pre-consolidation compared to post-consolidation, and therefore Hypothesis 5 is not supported.

Table 8. Regression Results for Hypothesis 5 Regression of Independent Acquirer Specialization Variable with *PMF* Dependent Variable

	Reduced Form Model (5)	Full Regression Model (5)
Variable	*PMF*	*PMF*
Specialization	-.0065	-0.01
	(0.0097)	(0.03)
Profit		0.04
		(0.97)
BankSize		1.33
		(6.89)
30-Year Fixed		3.17***
		(0.80)
2011		0.06
		(0.05)
2012		0.03
		(0.03)
2013		0.01
		(0.03)
2014		0.01
		(0.03)
2015		0.00
		(0.03)
2016		-0.01
		(0.03)
2017		0.01
		(0.02)
2018		0.02
		(0.02)
Intercept	0.13***	0.12***
	(0.01)	(0.03)
Model Statistics		
Adjusted R^2 (%)	0.00	-0.01
F-Statistic	0.46	0.77

N = 361. The coefficients are the top row; the robust standard errors are shown in parenthesis. ***, **, and * indicate that the coefficient estimates are different from zero at the .01, .05, and .10 probability levels, respectively, for a two-tailed test.

Table 9 describes both full and reduced form regression models estimates for Hypotheses 6 through 9. The key independent variable of interest is *Location* and its effect on dependent variables *QTY, AMT, PLA*, and *PMF*. The regression model estimate (6) results in Table 9 describe the effects of the listed independent variables on the dependent variable *QTY* for Hypothesis 6, in brief, states that there will be a greater number of mortgage loans originated post-consolidation as compared to pre-consolidation if the acquirer and target bank had headquarters in the same location pre-consolidation. The full regression model estimate (6) generates an F-statistic of 5.51 and significant at the 1% level, with a corresponding adjusted R^2 of 12%. The reduced form model and key individual coefficient for independent variable, *Location*, while consistent with my predicted direction, are not significant at the 10% level with a coefficient estimate of 153.89. Thus, the full regression model estimate does not support Hypothesis 6.

Regression model estimate (7) results in Table 9 describe the effects of the listed independent variables on the dependent variable *AMT* for Hypothesis 7, which in brief, states that there will be greater aggregate mortgage originations post-consolidation as compared to pre-consolidation if the acquirer and target bank had headquarters in the same location pre-consolidation. The full regression model yields an F-statistic of 2.88 with significance at the 1% level and an adjusted R^2 of 2%. The reduced form model and key individual coefficient for independent variable *Location* are not significant at the 10% level, with a coefficient estimate of 26.50, although consistent with my predicted direction. The full regression model estimate does not support Hypothesis 7.

Regression model estimate (8) results in Table 9 describe the effects of the listed independent variables on the dependent variable *PLA* for Hypothesis 8, which in brief, states that there will be higher per-mortgage loan amounts originated post-consolidation as compared to pre-consolidation if the acquirer and target bank had headquarters in the same location pre-consolidation. The full regression model estimate (8) generates an F-statistic of 1.32 and is not significant at the 10% level, with a corresponding adjusted R^2 of 1%. Further, the reduced form model and key individual coefficient for independent variable *Location* are not significant at the 10% level, with a coefficient estimate of -29.40, the opposite of my predicted direction. Accordingly, the full regression model estimate does not support Hypothesis 8.

The final regression model estimate (9) results in Table 9 describe the effects of the listed independent variables on the dependent variable *PMF* for Hypothesis 9, which in brief, states that there will be lower bank percent mortgage loan concentration post-consolidation as compared to pre-consolidation if the acquirer and target bank had headquarters in the same location pre-consolidation. The full regression model estimate reflects an F-statistic of .77 and is not significant at the 10% level, with an adjusted R^2 of 0%. Both the reduced form model and key individual coefficient for independent variable *Location* are not significant at the 10% level, with a coefficient estimate of 0.00%, inconsistent with my predicted direction. Thus, the full regression model estimate does not support Hypothesis 9.

Table 9. Regression Results for Hypotheses 6 through 9 Regression of Independent Bank Location Variable with Dependent Variables: *QTY*, *AMT* (in Millions), *PLA* (in thousands), *PMF*, *RFM*, and *FRM*

Variable	***RFM*** **(6)** *QTY*	***FRM*** **(6)** *QTY*	***RFM*** **(7)** *AMT*	***FRM*** **(7)** *AMT*	***RFM*** **(8)** *PLA*	***FRM*** **(8)** *PLA*	***RFM*** **(9)** *PMF*	***FRM*** **(9)** *PMF*
Location	-86.5981	153.89	-6.24	26.50	-17.9769	-29.40	0.00	0.00
	(355.4200)	(338.30)	(81.60)	(80.56)	(33.0400)	(33.40)	(0.01)	(0.01)
Profit		-7,778.36		557.28		333.81		0.03
		(27,093.08)		(6,452.05)		(2,674.81)		(0.97)
30-Year Fixed		5,917.88		2,537.90		-4,005.93***		3.04***
		(13,126.47)		(3.13)		(1,295.93)		(0.47)
BankSize		9.95***		0.02***		0.00**		1.24
		(1.96)		(0.00)		(0.00)		(6.91)
2011		-387.50		-133.33		189.35		0.05
		(1,217.81)		(290.01)		(122.60)		(0.04)
2012		-301.56		-125.48		43.34		0.05*
		(635.39)		(151.31)		(60.67)		(0.02)
2013		-839.67		-215.92		-13.75		0.02
		(535.81)		(127.60)		(53.25)		(0.02)
2014		-236.74		-58.64		-32.17		0.01
		(555.66)		(132.33)		(56.77)		(0.02)
2015		-277.65		-51.83		34.27		0.01
		(549.51)		(130.86)		(53.58)		(0.02)
2016		-494.48		-181.10		-10.45		0.00
		(538.44)		(128.23)		(50.72)		(0.02)
2017		699.05		43.79		-38.69		0.01
		(564.35)		(134.40)		(5.11)		(0.02)
2018		1,575.34**		173.14		77.22		0.00
		(547.30)		(130.34)		(59.26)		(0.02)
Intercept	491.8100***	233.16	105.48***	99.99	-162.91***	-157.83***	0.13***	0.12***
	(159.8300)	(517.18)	(36.69)	(123.16)	(14.86)	(51.06)	(0.01)	(0.02)
Model Statistics								
Adjusted R^2 (%)	-0.0026	0.12	0.00	0.02	0.00	0.01	0.00	-0.01
F-Statistic	0.0594	5.51***	0.01	2.88***	0.30	1.32	0.06	0.77

N = 361. The coefficients are the top row; the robust standard errors are shown in parenthesis. ***, **, and * indicate that the coefficient estimates are different from zero at the .01, .05, and .10 probability levels, respectively, for a two-tailed test.

Additional Results

To further examine the model results, I applied two robustness checks similar to Berger and Bouwman (2013). For the sake of brevity, these results are not reported but only discussed. The first robustness check, further defined as community bank robustness check, consists of bifurcating sample observations into subsamples of community and non-community banks using bank size of less than $1billion in total assets as the criteria for identifying a community bank. Banks with total assets greater than $1 billion are defined as noncommunity banks. Thus, an indicator variable *Community Bank* is established that is coded 1 or "Yes" if the bank size meets the criteria of less than $1 billion in total assets, otherwise the indicator variable indicates 0 or "No." I tested the community and noncommunity bank subsamples in the same manner as the combined sample of community and noncommunity banks full regression models. The results of the community bank robustness check confirm directionality of the findings of Hypotheses 1 through 9 and support a significance level of 1% for dependent variables *PLA* and *PMF*. Interestingly, the coefficient parameter estimates for the *Community Bank* robustness variable is significant at the 5% level when regressed against the *PLA* variable to test Hypothesis 5; otherwise, *Community Bank* is not significant at the 10% level. Subsequently, it does not appear that a size dimension of greater or less than $1 billion in total assets changes the influence of bank consolidation and the level of mortgage loan availability.

The second robustness check, further defined as the expanded event window robustness check, examines the event window of one year prior and two years past bank consolidation, rather than the event window of one year prior and one year past as established in my empirical design. The reason for the expanded event window robustness check is to test the influence of post-consolidation changes that may not manifest immediately in the year following a bank combination, as was examined in the original full regression models for Hypotheses 1 through 9. The results of the expanded event window robustness check confirm the findings of Hypotheses 3, 4, 8, and 9 regarding directionality and level of significance of the key variables of interest: *Consolidation, Specialization,* and *Location.* Interestingly, the expanded event window robustness test for Hypotheses 1 and 2 find an increase in *QTY* and *AMT* values post-consolidation, directionally opposite to the model results of Hypothesis 1 and 2 and inconsistent with my predicted change in value. By expanding the event window by an additional year, I find that Hypothesis 5, the recasting of the post-consolidation entity with a percent of mortgage loan focus, is directionally consistent with model results but the opposite of my predicted direction. The results of the expanded event window robustness test for Hypotheses 5 find coefficient parameter estimate *Specialization* significant at the 5% level, with an improvement in the adjusted R^2 of 2%, perhaps suggesting that acquiring firm recasting does exist when examined over a broader event window.

Both Hypotheses 6 and 7 are designed to focus on potential effects of relative location of acquirer and target headquarters and the impact on *QTY* and *AMT* post-consolidation. I find that the robustness test on *QTY* is directionally inconsistent with model results yet improves the adjusted R^2 from 12% to 17%. The coefficient parameter estimate *Location* is not significant at the 10% level, as observed in the full regression model. I also find the robustness test directionally inconsistent with model results on *AMT* post-consolidation yet improves the model's adjusted R^2 from 5% to 15%. The coefficient parameter estimate *Location* is not significant at the 10% level, as observed in the full regression model.

Overall, both robustness tests align with my model results with additional insight particularly with an expanded event window. I speculate that by increasing the post period to greater than $t + 1$, to perhaps $t + 3$, the predicted effects hypothesized in my study might provide additional explanatory power to the empirical tests.

Discussion

As banks continue to consolidate at a rate of 250 bank mergers per year,[2] increased focus on the economic implications of bank consolidation encourages scholars to examine the effects of bank credit on the communities they serve. The concentration of extant research is on the effects of consolidation in relation to small business lending, with earlier studies concluding with mixed results as to whether U.S. banks substantially reduce the supply of credit post-consolidation (Berger et al., 1998; Strahan & Weston, 1998; Weston & Strahan, 1996; Walraven,1997; Jagtiani & Lemieux, 2016). It is difficult to ignore the parallels of mortgage and small business lending declines of loan portfolio composition of both types of loans to total assets. In a study by the FDIC over the periods 1984 through 2011, mortgage lending to total assets fell by 2%, while business lending fell by 6% (FDIC, 2020). Both forms of lending are subject to competition from nonbank lenders such as credit unions, independent mortgage companies, and Fintech

[2] FDIC annual historical bank data from 2008 to 2019 include commercial and industrial banks (national banks, state-chartered banks, state-charted banks that are nonmembers of the Federal Reserve System, FDIC-supervised state savings banks, OCC-supervised state savings banks, federal and state savings and loans). The dataset excludes non-FDIC insured commercial banks, thrifts, and credit unions.

organizations (Carter & McNulty, 2005). A recent study by Jagtiani and Maingi (2018) builds on research by Berger et al. (1998) and Peek and Rosengren (1998), concluding that bank consolidations negatively impact the supply of small business credit and, to a greater extent, when the proximity of headquartered operations and propensity of lending of the acquirer differ from that of the target pre-consolidation.

With the foundation of studies by Jagtiani and Maingi, (2019), Peek and Rosengren, (1998), and Berger et al. (1998) on bank consolidations and small business lending, I build upon similar analytical logic but substitute small business lending with mortgage lending to determine any potential consumer mortgage lending gaps.

My research was designed to test the relationship of bank consolidation and the quantity, aggregate amount, per-loan amount, and percent of mortgage lending concentration by banks. I anticipated a decline in the number of mortgage loans, aggregate amount of mortgage loans, and percent of mortgage lending concentration by bank firms post-consolidation. In contrast, I anticipated an increase in the per-loan amount post-consolidation. As with prior research, I also subjected my models to the influences of acquirer specialization and headquarter location moderators to determine additional effects from consolidation on quantity, amount, per-loan amount, and percent of mortgage lending concentration (Jagtiani & Maingi, 2019). My expectation of the specialization and location moderators was that they would compound the negative effects of consolidation.

My economic rationale for predicting declining mortgage lending was based on increased regulatory costs, changes in financial and information technology, and the commoditization of retail lending through increased competition from nonbank entities

(FDIC, 2020). My hypotheses were developed to test four main dimensions of change with pre- and post- bank consolidation. Unfortunately, none of the nine hypotheses was fully supported by my study. However, the model results of the key individual *Consolidated* coefficient's impact on Hypotheses 3 and 4 are significant at the 1% level, although contrary to my predicted direction. My study reveals that firms subject to consolidation are more likely to originate lower average mortgage loans post-consolidation as compared to pre-consolidation. In addition, firms post-consolidation appear to increase their focus more on mortgage lending than prior to the consolidating event. While contrary to my expectations, these findings suggest that bank consolidations have beneficial impacts on mortgage lending.

The catalyst for embarking on a bank consolidation strategy are numerous, such as the efficiency and focusing hypotheses designed with the intent of increasing the combined value of merging banks (Berger & Humphrey, 1990). Perhaps consolidation is part of an overarching bank growth strategy that also includes increased profitability that can be achieved in part by loan optimization through improved credit management (Forcarelli et al., 2002). My economic rationale for higher per-loan amounts was based on recent trends in the increase of jumbo loans due to their higher credit requirements and lower likelihood of default, thus providing a safer mortgage lending option relative to conventional loans. However, when paired with the findings of Hypothesis 4, an increase in the percent concentration of mortgage loans to total loans, it could be argued that banks may be pursuing a strategy similar to nonbank mortgage lenders, as nonbank mortgage lenders focus on selling or securitizing loans to free up capital and limit risk. Therefore, lower per-loan amounts are more likely to be candidates for securitization since jumbo loans typically do not meet the criteria for securitization. I suspect that consolidated banks are more likely to pursue a securitization strategy in an effort to improve profitability through the post-consolidation combined economies of scale and mortgage loan focus compared to nonconsolidating banks. Admittedly, nonconsolidating banks may also pursue greater securitization of their mortgage portfolios to improve profitability if appropriate. Consequently, a securitization strategy is not predicated on the consolidation of a bank but rather a competitive strategy designed to compete with nonbank rivals. Further, the percent concentration of mortgage loans to total loan increases can also be a manifestation of a decline in other forms of lending such as small business lending relative to total loans. Unfortunately, traditional banks or smaller sized banks have limited lending vehicles in an increasingly competitive marketplace.

Conclusion

The magnitude and implication of mortgage lending on the U.S. economy and communities cannot be overstated. In 2020, for example, $11.05 trillion in mortgages were outstanding and another $1.9 trillion funded (Mortgage Bankers Association, 2022) reflecting the level of mortgage debt of approximately 70% of all household debt (Catanzaro, 2020). Although my research did not produce any fully supported hypotheses, it contributes to extant literature as to the effects of consolidation on mortgage lending along with small business lending by addressing the research questions of whether post-consolidated entities create consumer mortgage loan credit gaps. Hypotheses 3 and 4 findings suggest that contrary to my prediction of higher average loan amounts and banks moving away from mortgage lending relative to total lending, the relationships of lower average loan amounts and an increased focus on mortgage lending prevail. Consumers are more likely to benefit from lower average loan amounts and thus have more access. In addition, the increased focus towards mortgage lending at consolidated banks further compounds the likelihood of greater mortgage credit availability, contrary to the notion of reduced mortgage availability. My findings also support the on-going policy strategy of the Consumer Financial Protection Bureau's (2013) "Ability-to-Repay/Qualified Mortgage Rule" under the Truth in Lending Act (Regulation Z).[3] The rule in general states that creditors that provide mortgage loans will have to determine that the consumer has the ability to repay the loan. Additional amendments to the Repay/Qualified Mortgage Rule aim to increase lower average loan amounts and focus on mortgage lending, including amendments relating to small creditors and rural or underserved areas as well as amendments to revise the definition of qualified mortgages (QMs). QMs require the ratio of a consumer's total monthly debt to total monthly income or debt-to-income (DTI) ratio not to exceed 43%, an amendment ratified in December 2020 that replaces the DTI ratio with price-based thresholds (Consumer Financial Protection Bureau, 2020).

Prior literature focused on consolidation and small business lending, in part due to readily available FDIC public data. This is the first study that links a mortgage lending dataset, HMDA, with the bank structural and financial data of the FDIC. In doing so, I created a rich dataset of public data from two U.S. institutions that can be leveraged for future research both for policy makers and academics.

Although the sample study included 5,158 observations, there were study limitations regarding the combination of the HMDA and FDIC dataset. Unfortunately, 39% of

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[3] Creditors are required to make reasonable and good faith determinations of consumers' ability to repay a residential loan according to its terms.

combined HMDA and FDIC observations remained unmatched and were excluded from the final sample; this may have led to less significance for differences in post- and pre-consolidations.

Another study limitation was the relative size disparity of target and acquiring banks involved in consolidation events included in the sample that potentially limited the magnitude of change in quantity and amount of loans observed. The bank size limitation was further described in the univariate analysis as the mean range differences of pre- and post-event data, which was much greater than that of median range differences of sample bank total assets. Accordingly, the full-form models controlled for banks size across the entire sample but not for the size disparity of acquiring banks to target banks.

Finally, my experimental design observed the change in pre- and post-consolidation of quantities and mortgage loan amounts in a static environment or static effect, which is designed to focus on balance sheet changes alone (Berger et al., 1998). In addition, my study captured the direct effects, the change in percent mortgage concentration to total loans post-consolidation. However, the study is limited by not including the restructuring effects that also occur in banks' post-consolidated financial conditions, asset sizes, and competitive positions. As a result, the static and direct effects may underestimate the influence a restructuring effect has on the originations of mortgage loans.

Future research studies may continue to focus on the size effect of large versus smaller banks post-consolidation as larger banks are now too big to fail and smaller banks may continue to combine with other smaller banks to remain relevant. Opportunities for future research, in particular regarding mortgage lending and bank consolidation, may segment banks on more than an asset size criterion, such as number of loans, type of loans, firm profits, and by expanding the post-consolidation event window multiple years out to determine whether an acquirer's lending culture prevails. Lastly, future research could determine the dynamic effects of mortgage lending by including static, restructuring, and direct effects with the inclusion of how bank consolidation impacts changes in mortgage lending within nonbank institutions such as credit unions, independent mortgage companies, and Fintech organizations.

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APPENDIX: VARIABLE DEFINITIONS

Dependent Variables Quantity of Mortgage Loan Origination (QTY)	Calculates the change, $\Delta y_{n,i,\ (t+1)-(t-1)} = (y_{n\ t+1} - y_{n\ t-1})_i$ in the quantity of home mortgage loans originated post-consolidation $y_{n_{t+1}}$ period less the quantity of home mortgage loans at origination pre-consolidation $y_{n_{t-1}}$ by bank$_i$ where y_n equals the quantity of home mortgage loans.
Dollar Amount of Mortgage Loan Originations (AMT)	Calculates the change, $\Delta y_a = (\sum y_{a\ t+1} - \sum y_{a\ t-1})_i$ in the aggregate home mortgage loan amount at origination post-consolidation period $\sum y_{a_{t+1}}$ less the aggregate home mortgage loan amount pre-consolidation period $\sum y_{a_{t-1}}$ by bank$_i$ where y_a equals mortgage loan amount.
Per Loan Amount (PLA)	Calculates the change, $\Delta y_{a/n} = \left((\sum y_{a_{t+1}}/y_{n_{t+1}}) - (\sum y_{a_{t-1}}/y_{n_{t-1}}) \right)_i$ in the per mortgage loan amount at origination post-consolidation period less the per mortgage loan amount at origination pre-consolidation where y_a equals mortgage loan amount and y_n equals the quantity of home mortgage loans.
Percent Mortgage Loan Focus (PMF)	Calculates the change, $\Delta y_{\%i} = ((\sum y_{aml\ t+1}/\ y_{atl\ t+1}) -$ weighted average $(\sum y_{caml\ t-1}/\ y_{catl\ t-1}))_i$ in% of the proportion of mortgage loans (y_{aml}) to total loans (y_{atl}) post-consolidation period less the weighted average of the combined proportion of mortgage loans (y_{caml}) to combined total loans (y_{catl}) pre-consolidation.
Independent Variables Consolidated	Indicator variable used to assess the impact of bank consolidation on various dependent variables. Coded as 1 for "yes" and 0 for "no" in the event a bank consolidation occurred in year t.
Specialized	Indicator variable used to assess the impact of acquirer mortgage loan specialization on the sample set of consolidated banks. Coded 1 or "Yes" if the ratio of mortgage loans to total loans pre-consolidation is greater for the acquiring bank compared to the ratio of the target bank, otherwise the indicator variable indicates 0 or "No"

Location	Indicator variable used to assess a proximity of acquirer and target bank before consolidation. If the target and acquiring banks have headquartered operations in the same city prior to consolidation, 1 indicates “yes” and 0 indicates “no”.
BankSize	Pre-consolidation of bank profitability calculated by net income/ total assets.
Control Variables Profit	Pre-consolidation of bank size as measured by total assets
30-Year Fixed Rates	Pre-consolidation of 30-year fixed interest rate mortgage loans
Calendar Year Fixed Effect	Indicator variable used to control for any time trend changes in the dependent variables for periods 2010 - 2020

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