Strategic Acquisitions Amongst Financiers in the Intangible Economy*

Suleyman Gozen † David Hong ‡ Mehmet Furkan Karaca §

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Abstract

The banking industry has seen significant growth in mergers and acquisitions (M&A) and intangible assets over the last decades. This paper investigates how the accumulation of intangible assets influences bank M&A strategies. We first reveal three key empirical findings: (i) the intangible asset ratio in the banking industry has increased five-fold over the last thirty years, (ii) there is strong assortative matching in M&A transactions, with acquirer banks tending to merge with target banks that share similar characteristics, such as size, loans, net interest income, and intangible assets, and (iii) considering the cyclicality of bank M&A activity and assortative matching, this matching appears to be a general phenomenon rather than a time-specific pattern. Next, we conduct a causal analysis using a difference-in-differences framework to estimate the effect of bank M&As on performance through the channel of intangible asset synergies. We find that M&A activity has a positive causal impact on bank loan growth and operating efficiency gains, particularly for transactions with higher intangible asset synergies. Further, we employ a search model to ground our empirical evidence and outline the conditions under which assortative matching occurs pre-merger and how intangible asset synergies lead to efficiency gains post-merger.

Keywords: Intangible Assets, Bank Mergers and Acquisitions, Assortative Matching

JEL Codes: E22, E44, G21, G34

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†School of Economics, University of Bristol. Email: suleyman.gozen@bristol.ac.uk.

‡School of Economics, The University of Edinburgh. Email: dhong@ed.ac.uk.

§Essex Business School, University of Essex. Email: m.f.karaca@essex.ac.uk.

1 Introduction

The sharp rise in mergers and acquisitions (M&A) among U.S. commercial banks over the last four decades has drawn substantial research attention. During this period, the U.S. economy has transitioned towards a knowledge-based economy resulting in a significant increase in the role of intangible capital in the production process. This phenomenon has been studied in the context of non-financial firms. We observe a similar trend in the banking industry. The FDIC Annual Historical Bank Statistics reveal that aggregate intangible assets have surged from \$2.8 billion in 1985 to over \$376 billion in 2020. Moreover, the FDIC records also show the total number of registered commercial banks decreased from around 14,000 to around 4,000 in the same period. Given the documented facts on the rise of intangible assets and consolidations in the financial sector, this paper explores the crucial question of how intangible assets influence bank M&A strategies and post-merger performance. By examining the synergy created through intangible assets, our study aims to better understand the strategic considerations underpinning bank mergers and acquisitions and their outcomes in the evolving financial landscape.

We explore the distinct features of intangible assets in the context of banking M&A activities. Unlike tangible assets, intangible assets can be more easily deployed across different lending markets, potentially leading to higher synergy gains . A pertinent example of this is organizational assets, a crucial component of intangible assets that encompasses intrinsic characteristics of a bank, such as brand value and lending culture. Such intangible assets in financial intermediaries have significant potential to enhance operating efficiency and loan growth thereby providing strong incentives for banks to seek synergistic benefits through consolidations.

This paper examines several questions: To what extent does intangible asset accumulation occur among banks? Through which channels do intangible assets influence bank M&A activities and strategies? What are the general characteristics and patterns of bank M&A in the context of intangible assets? To what extent do intangible asset synergies in bank M&A affect post-merger performance? We develop both an empirical and theoretical framework to provide a comprehensive analysis examining the role of intangible assets in shaping bank M&A dynamics and outcomes. To the best of our knowledge, our paper is one of the first studies that provides a deeper understanding of the role of intangible assets in financial consolidations.

Using various databases such as U.S. Call Reports and bank mergers and acquisitions data, we document three key stylized facts: (i) the banking industry has experienced a five-fold increase in the intangible asset ratio over the past thirty years, (ii) there is strong assortative matching in M&A transactions, where acquiring banks tend to merge with target banks that share similar characteristics such as size, loans, net interest income, and intangible assets, and (iii) considering the cyclicality of bank M&A activity and assortative matching, this matching appears to be a general phenomenon rather than a time-specific pattern.

For the first stylized fact, we document that the bank-level intangible asset (excluding goodwill) ratio increased by a factor of approximately five from the 1980s to the 2010s. This suggests that banks are positioning themselves to benefit from the rising importance of intangible assets. We also investigate the time variation of the main components of intangible assets, namely goodwill and other intangible assets (such as mortgage servicing rights and purchased credit card relationships) in the banking industry, along with tangible assets. We observe that the annual average of total intangible assets has been higher than that of tangible assets since the early 2000s. Moreover, even though goodwill seems to be a main component of total intangible assets, the role of other intangible assets also appears significant.

For the second stylized fact, acquirer banks tend to merge with target banks that exhibit similar financial metrics, such as total loans and net interest income. Specifically, acquirer banks with higher (lower) total assets, loans, and net interest income are more likely to merge with target banks with higher (lower) total assets, loans, and net interest income. Additionally, we show the levels of intangible assets are an important driver in M&As. Finally, we analyze the dynamics of assortative matching over time and find that it is a general phenomenon, not specific to any particular period.

To document empirical evidence of assortative matching in bank M&A transactions, we construct hypothetical mergers that could have occurred and compare them with actual mergers. We first find that random pairings of banks are not expected to exhibit assortative matching, whereas real bank M&A transactions are strategically planned and sorted. However, the direction of assortative matching could have remained ambiguous. U.S. bank consolidations could reflect strategic substitutability. That is, the greater the difference in characteristics between a target and acquirer bank, the likelier they engage in a M&A. While strategic complementarity would be in the opposite direction. Our empirical strategy confirms a strong and significant presence of assortative matching between acquirer and target banks in the direction of strategic complementarity, with intangible assets being a significant characteristic.

For the third stylized fact, we examine the cyclicality by comparing recession and non-recession periods in the U.S. economy to determine whether our findings are time-specific or represent general phenomena. We do not find strong or significant evidence that the cyclical pattern of the aggregate economy plays a key role in explaining assortative matching in bank M&A transactions. Thus, assortative matching in bank M&A transactions appears to be a general phenomenon rather than a time-specific pattern.

To investigate the role of intangible asset synergy and provide evidence of its post-merger performance, we conduct a causal analysis using a difference-in-differences framework. In line with the approach used in related literature, the treated group consists of acquirer banks involved in successful M&A deals and the control group consists of acquirer banks whose M&A deals were terminated or withdrawn. We analyze their annual growth in loans and operating efficiency during the pre- and post-merger periods and find that: (i) there is a parallel trend in loan and operating efficiency growth during the pre-merger period, and (ii) the treated group (acquirer banks in successful M&A deals) experiences statistically significant higher annual growth in loans and operating efficiency than the control group (acquirer banks in terminated or withdrawn M&A deals) post-merger. This higher growth persists for at least five years after the M&A. In terms of intangible asset synergy, we find M&A deals that involve higher assortative matching in intangible assets exhibit relatively higher and statistically significant growth in loan and operating efficiency. In contrast, we do not find such evidence for acquirer banks with lower assortative matching in intangible assets. Thus, we demonstrate that the overall post-merger efficiency gains in loan and operating efficiency growth are primarily driven by intangible asset synergy.

To substantiate our empirical evidence, we develop a theoretical search model of bank M&A, illustrating how intangible asset synergies influence bank consolidation patterns. We present a continuous-time Diamond-Mortensen-Pissarides search model of bank M&A, where lending and operational costs are modeled as a function of the banks' intangible asset stock. Our model examines strategic interactions in banking consolidations and endogenously incorporates intangible asset synergies into the assortative matching process. We establish the assortative matching equilibrium, "like-buys-like," and present hypotheses regarding the likelihood of assortative matching and its implications for various balance sheet statistics, both pre- and post-merger. Our model propositions outline the conditions under which assortative matching occurs pre-merger and how intangible asset synergies lead to efficiency gains post-merger. These insights are crucial for understanding the characteristics and dynamics of strategic interactions, as well as for improving policy evaluations related to bank consolidations.

Based on the model's equilibrium outcomes, we employ counterfactual analyses through simulations to examine the impact of regulatory policies on assortative matching and post-merger efficiency within the banking sector. First, we explore how changes in the regulatory environment affect the likelihood of achieving assortative matching. We find that stricter regulations that inhibit entry into the merger state can lead to a breakdown in assortative matching. The second simulation illustrates the post-merger efficiency gains under assortative matching with varying parameters. We find that assortative matching is not carte blanche guaranteeing positive efficiency gains; rather, specific parameter regions should be scrutinized. Together, these simulations provide valuable insights into how regulatory frameworks shape merger patterns and influence the overall efficiency of the banking sector.

The insights based on our empirical evidence and theoretical framework have important policy-related implications, particularly in light of the increased regulatory attention on bank M&A activities. As the regulatory landscape evolves, there is growing concern about the potential risks of market concentration and its impact on consumer choice and financial stability. Recent interagency coordination efforts by the Federal Deposit Insurance Corporation (FDIC), Office of the Comptroller of the Currency (OCC), and Department of Justice (DoJ), culminating in new bank merger review policies announced on September 17, 2024, reflect a heightened emphasis on ensuring that M&A activity does not lead to anti-competitive behavior or the disproportionate consolidation of market power in a few large institutions. However, the positive effects we identify—specifically, the persistent loan growth and operating efficiency gains driven by intangible asset synergies—suggest that strategic M&A decisions can deliver long-term benefits to the financial system. These synergies result in improved lending capacities and enhanced operational efficiencies, potentially mitigating concerns that M&As will lead to reduced consumer choice or increased risks of market concentration. Our findings indicate that intangible assets, which have traditionally been underexplored in M&A analyses, play a critical role in driving the post-merger success of acquiring banks.

Related Literature The literature on bank mergers and acquisitions is expansive and includes theoretical and empirical contributions. Our attention will be focused on the recent advancements in the literature. For a more thorough examination, we refer the reader to look at DeYoung et al. (2009) as they provide a comprehensive summary of the literature starting from the 2000s and earlier. Our work contributes to the literature in several ways.

First, our study relates to the literature on bank mergers and acquisitions' determinants (or motivations). Bliss and Rosen (2001) links bank consolidation decisions with CEO compensation and finds the type of compensation matters. In particular, acquisitions are less likely to occur when CEOs receive more stock-based compensation. Thus, managerial incentives can be a relevant factor. A possible motivator for banks to engage in bank consolidations is because it is deemed ex-ante profitable to do so. Focarelli et al. (2002) examines bank mergers and acquisitions across Italy and finds mergers aim to boost income from services and improve return on equity by reducing capital requirements and also restructure their loan portfolios through acquisitions, leading to higher profits through improved or expanded lending practices. Alessandrini et al. (2008) complements those findings by finding evidence using Italian data that negative present value lending activities occurring in acquired banks are eliminated. From the perspective of an acquirer or acquiree, Beccalli and Frantz (2013) finds bank size, cost-efficiency, and growth as the main determinants of a bank's role. Larger banks with high cost-efficiency and a strong growth history are more likely to be the acquiring entities in an M&A deal. Levine et al. (2020) finds when banks have greater overlap in geographic locations of their bank branches, there is a higher probability of a merger. This suggests potential cost savings from eliminating redundant operations. The statistical inference of the above papers may be in doubt when stock market data is unavailable. Akkus et al. (2016) presents a matching market framework with revealed preferences for merging banks that do not rely on stock market data and finds the value-creation of bank M&A deals is due to improved cost-efficiencies and network effects. Thus, the findings of previous papers appear to be robust. A possible constraint on bank M&A deals is regulatory constraints. Bindal et al. (2020) finds U.S. banks that are just below the size threshold defined by the Dodd-Frank Act are more likely to be acquirers and ex-post reduce small business lending due to the higher regulatory burden. Carletti et al. (2007) finds stricter regulation on mergers and acquisitions across the European banking system decreases the likelihood of creating consolidated banks that are deemed "too big to fail." The prior research above has not emphasized the importance of intangible assets. Our contribution aligns with intangible assets being an important determinant for bank M&As.

Second, our work is related to the extensive research on post-M&A bank performance. Earlier and recent literature on this topic has found mixed results, suggesting that ex-ante motivations for bank consolidation do not translate to ex-post performance. Rhoades (1993) found for the period between 1981 and 1986, horizontal bank mergers did not lead to improved efficiency gains as it was predicted. Peristiani (1997) found for the period from 1980 to mid-1990s no evidence of improvement in X-efficiency of acquirers and a slight improvement in scale efficiency for acquiring banks post-merger. Bliss and Rosen (2001) argue that bank mergers during the late 1980s and early 1990s typically did not lead to improvements in relative operating performance or positive abnormal returns for acquiring bank shareholders. Cornett et al. (2006) found a significant increase in the industry-adjusted operating performance of merged banks during the post-merger period, with relatively greater performance gains for consolidations between large banks than small banks. Levine et al. (2020) found banks with significant branch network overlap record higher post-merger returns. We establish causal evidence that intangible asset synergy affects post-M&A bank performance on loan growth and efficiency improvements.

Layout We organize the paper as follows: Section 2 introduces the databases used to investigate intangible assets in the banking industry and assortative matching in bank M&As. Section 3 provides empirical facts on intangible assets and assortative matching in banking. Section 4 presents the causal analysis framework and evidence on the role of intangible assets synergy in post-merger bank performance. Section 5 introduces the model framework. Section 6 characterizes the model's equilibrium and discusses its implications. Finally, Section 7 concludes by summarizing the key results and discussing policy-related perspectives.

2 Data

This section describes the different data sources used in the paper. Bank attributes, financials, and successful M&A deals are obtained from the Banking Suite (previously Bank Regulatory) in Wharton Research Data Services (WRDS). The source of the attributes and M&A deals data is the National Information Center (NIC). Financial data is derived from U.S. Bank Call Reports. We use Legacy Call Reports data, which covers a longer time period (1976-2020) compared to the new Call Reports dataset, which only starts from 2001. In addition, we obtain terminated bank M&A deals from the S&P Global - Capital IQ database and withdrawn bank M&A deals from the SDC Platinum M&A database through Refinitiv Eikon.

Bank Attributes Bank structure data provides information on active banks, branches, and closed banks. We use the structure data to locate banks and identify bank holding companies (BHCs). The parent companies (BHCs) of target and acquirer banks can be identified using attributes data. Hence, we can distinguish if a deal is a merger, or a bank acquisition, or a branch acquisition (reorganization).

Bank Financials We construct fundamental financials for banks following Drechsler et al. (2017, 2021). The dataset contains quarterly information from the income statements and balance sheets of all U.S. commercial banks, with unique bank identifiers. In the full sample, there are 20,774 unique commercial banks, 13,207 unique bank-holding companies, and 1,736,233 bank-quarter observations. Table A.2 presents the summary statistics for selected bank-level quarterly variables from the U.S. Call Reports.

Bank M&As Bank transformations data include unique identifiers for predecessor (target) and successor (acquirer) banks, transaction date and type, and the accounting method used for the transaction. We match acquirer and target banks to merger and acquisition data using bank identifiers. The data contains information on all bank mergers and acquisitions that have occurred since 1976. In addition, the top holding (parent) companies can be identified for both the non-surviving and surviving entities. Since our paper focuses on conventional and traditional mergers and acquisitions, we apply the following sampling procedures: (i) We only consider commercial bank (*charter type* $= 200$) M&A transactions; (ii) we only consider M&A deals where the charter is either discontinued or retained (*transformation code* $= 1\& = 9$), dropping other M&A deals, such as bank failures (*transformation code*$= 50$) under government assistance; and (iii) we only consider M&A deals where non-surviving and surviving entities have different top holding companies, thereby dropping M&A deals occurring within the same top holding companies. As a result of our sampling procedures, the bank M&A sample includes 7,793 M&A deals, 3,219 unique acquiring commercial banks, and 2,483 unique acquiring bank holding companies. After applying further sampling restrictions mentioned in Section 4, our final sample of completed (successful) M&A deals used in our causal analysis consists of

211 unique deals at the bank-holding company level.

Table A.3 documents the summary statistics of the number of M&A deals per year at the bank holding company level. Figure B.1 shows the histogram of the number of M&A deals per year at the bank holding company level.

Since our paper conducts a causal analysis and constructs a control group, we also use additional databases on bank M&A deals that are either terminated or withdrawn, which constitute our control group. We utilize terminated bank M&A deals from the S&P Global - Capital IQ database and withdrawn bank M&A deals from the SDC Platinum M&A database through Refinitiv Eikon. In both databases, we can observe the termination or withdrawal dates, along with unique identifiers for both acquirer and target entities. We also apply similar sampling procedures and further procedures, as mentioned in Section 4, to the deals in these two databases, where applicable, as we do for the successful M&A deals mentioned above. Our final sample used in our causal analysis consists of: (i) 48 terminated bank M&A deals, and (ii) 14 withdrawn bank M&A deals.

Bank Intangible and Tangible Assets As our paper emphasizes the importance of intangible assets in bank M&A activities, we construct intangible assets very carefully following financial reporting guidelines. We mainly use RCFD and RCON series from Call Reports to construct intangible assets. RCFD provides variables for banks with domestic and foreign branches and RCON includes variables for banks with only domestic branches. The reason for combining two series is to fill as many missing observations as possible to construct a better panel. Some missing items in RCFD series are reported in RCON series for domestic banks.

The main item for intangible assets in call reports is *Intangible Assets* (*RCFD2143 or RCON2143*). We use *RCFD2143* (or *RCON2143*) whenever it is available and when it is not, we reconstruct it using subitems according to reporting guidelines. We track available subitems over time following the changes in reporting guidelines, and calculate intangible assets. Broadly there are two subitems that we can use: Goodwill and Other Intangible Assets. *Goodwill* (*RCFD3163 or RCON3163*) is always included in the reporting guidelines. However, reporting of other intangible assets has changed over time. *Mortgage Servicing Assets* (*RCFD3164 or RCON3164*) and *Other Identifiable Intangible Assets* (*RCFD3165 or RCON3165*) are reported separately until 2001. *Purchased Credit Card Relationships* (*RCFD5506 or RCON5506*) and *All Other Identifiable Intangible Assets* (*RCFD5507 or RCON5507*) are reported as subitems of *Other Identifiable Intangible Assets* (*RCFD3165 or RCON3165*) during 1990s until 1998. Starting from 2001, *Other Intangible Assets* (*RCFD0426 or RCON0426*) is reported to represent all intangible assets other than goodwill. *Mortgage Servicing Assets* (*RCFD3164 or RCON3164*), *Purchased Credit Card Relationships and Nonmortgage Servicing Assets* (*RCFDB026 or RCONB026*), and *All Other Identifiable Intangible Assets* (*RCFD5507 or RCON5507*) are reported as subitems of Other Intangible Assets.

Moreover, we calculate Tangible Assets as the sum of *Premises and Fixed Assets (including capitalized leases)* (*RCFD2145* or *RCON2145*) and *Other Real Estate Owned* (*RCFD2150* or *RCON2150*).

To ensure the measures are suitable for economic interpretation, we drop negative values of tangible assets, intangible assets and its components. Table A.4 presents the summary statistics of the intangible asset components and tangible assets in the quarterly U.S. Call Reports. Since our paper focuses on intangible asset synergies in bank M&A deals, the goodwill component of intangible assets is excluded from our analysis, as it does not represent the synergy aspect we investigate. For instance, managers might have incentives to inflate the purchase price, which reflects onto goodwill (Ramanna, 2008, Shalev et al., 2013). Additionally, Masulis et al. (2023) show that goodwill does not significantly influence acquirer announcement returns. Thus, it is important to separate the impact of goodwill, which might represent other incentives, from the impact of other identifiable intangible assets. Therefore, following related studies that apply a similar approach, we focus primarily on other intangible assets (hereafter referred to as "intangible assets"), which will be the key variable of interest in the following empirical sections. Figure B.2 documents the histogram of the logarithm of intangible assets.

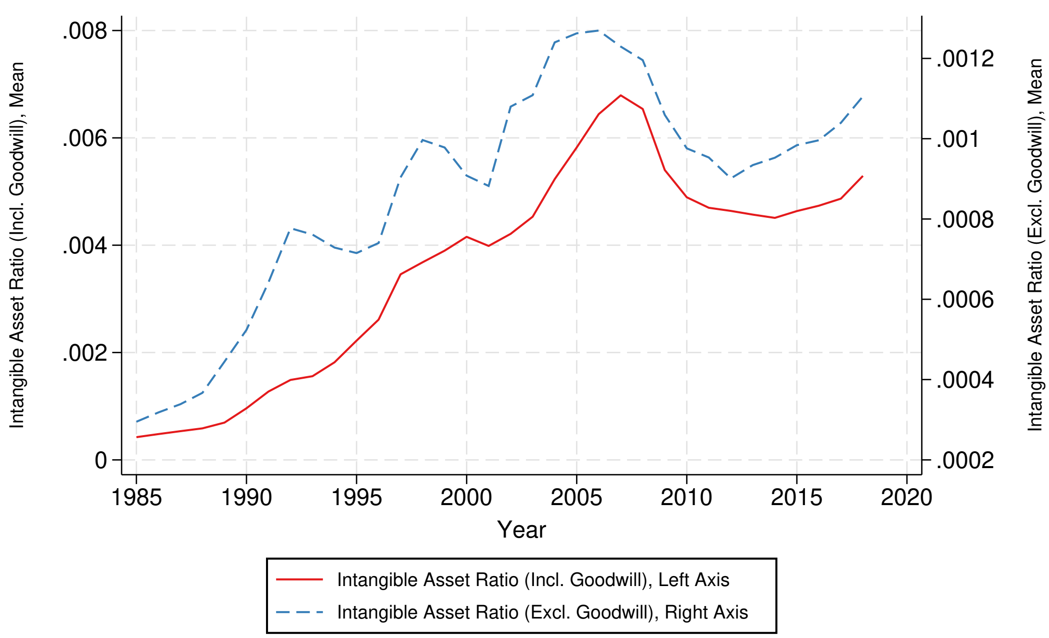
3 Empirical Facts

In this section, we provide stylized facts and empirical evidence on the role of intangible assets in assortative matching in bank M&As. First, we document several facts regarding the increasing share of intangible assets in the banking industry within the U.S. economy. Second, we provide empirical evidence on assortative matching in bank M&As along the dimensions of key balance-sheet variables and intangible assets. Third, we investigate the cyclicality of bank M&As and assortative matching to determine whether these are time-specific or general phenomena.

3.1 Intangible Assets in Banking

This section provides stylized facts on the rising importance of intangible assets in the banking industry within the U.S. economy.

Figure 1: Intangible Asset Ratio

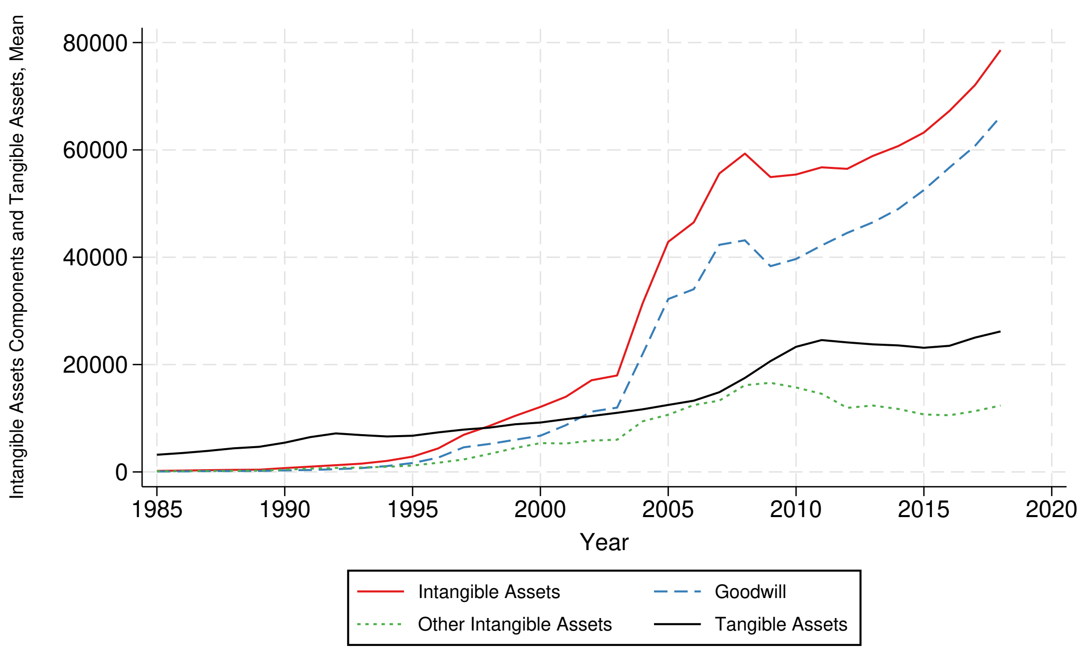


Note: The figure shows the simple annual average of intangible asset ratio for the banking industry. Intangible asset ratio is defined as $\frac{\text{Intangible assets}}{\text{Total assets}}$.

Using the constructed measure of intangible assets from U.S. Call Reports, Figure 1 documents that banks exhibit a rising ratio of intangible assets—including goodwill—growing from approximately 0.1% in the 1980s to around 0.8% in the 2010s. Additionally, the ratio of intangible assets—excluding goodwill—has increased from about 0.02% in the 1980s to approximately 0.1% over the same sample period. In other words, the former increased by a factor of approximately 8, while the latter increased by a factor of approximately 5 during a period of around 30 years.

Figure 2 documents the time variation of the main components of intangible assets, namely goodwill and other intangible assets (such as mortgage servicing rights and purchased credit card relationships) in the banking industry, along with tangible assets. We first observe that the average intangible assets became higher than the average tangible assets after the early 2000s. Second, even though goodwill seems to be a main driver of total intangible assets, the role of other intangible assets is also significant.

Figure 2: Intangible Asset Components and Tangible Assets



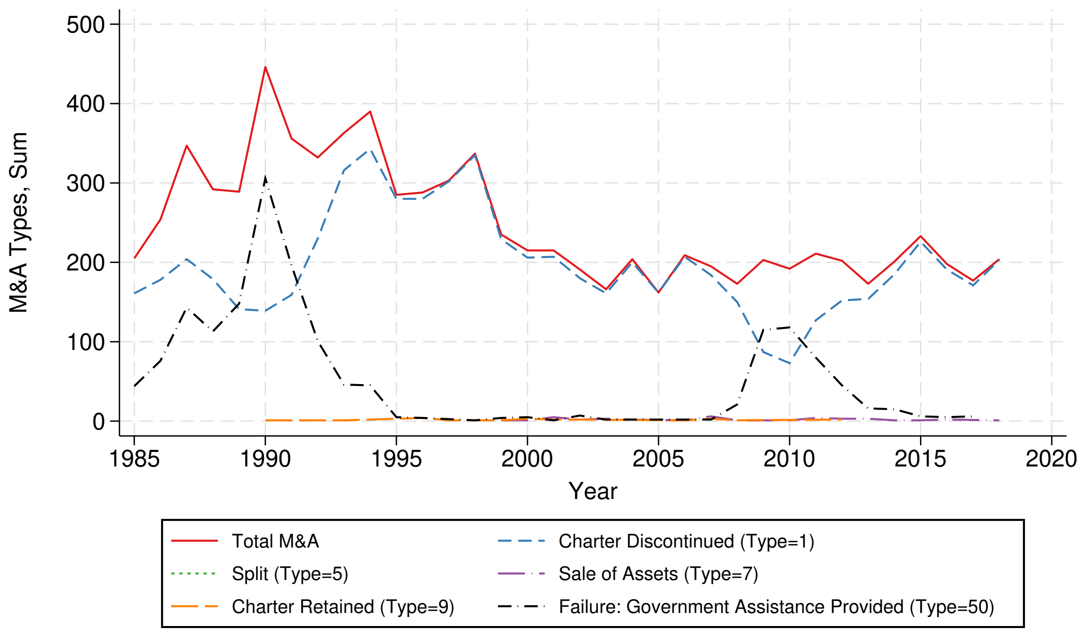
Note: The figure shows the simple annual average of intangible asset components and tangible assets for the banking industry.

3.2 Stylized Facts on Assortative Matching in Bank M&As

In this section, we first document the trends in banking M&As and provide evidence of the existence of assortative matching in banking M&As.

Trends in Bank M&As Figure 3 documents the annual sum of total number of M&As by different M&As types in the FDIC Call Report database.

Figure 3: Bank M&A Types



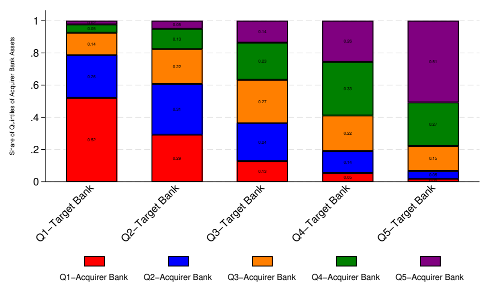
Note: The figure shows the simple annual sum of the total number of M&As by different types in the bank M&A database, after excluding M&A deals in which the acquirer and target banks belong to the same bank holding company.

We observe a striking increase in the total number of M&As between 1980 and 1990, which coincides with the episode of financial deregulation in the U.S. economy. The number starts to decrease after 1990, whereas the amount is still sufficiently high. We also observe that the type of M&A classified as "*Failure: Government Assistance Provided*" spikes during the 1991 and 2008 financial crises. This trend during recession periods would offer important insights. For instance, Granja et al. (2017) demonstrates that during the

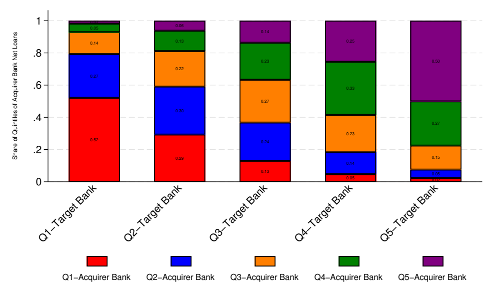
Great Recession, the allocation of failed banks was distorted by poorly capitalized potential acquirers, who faced a gap between their willingness and ability to pay, leading to significant resolution costs for the FDIC and suggesting important considerations for the bank resolution process. However, since our paper focuses on traditional bank M&As, we will concentrate only on the types of M&As classified as *"Charter Discontinued"* and *"Charter Retained"*.

Assortative Matching in Bank Characteristics After merging the U.S. Call Reports with bank-level M&A data, we are able to observe the pairwise information of various bank characteristics (acquirer bank - acquiree/target bank pair).

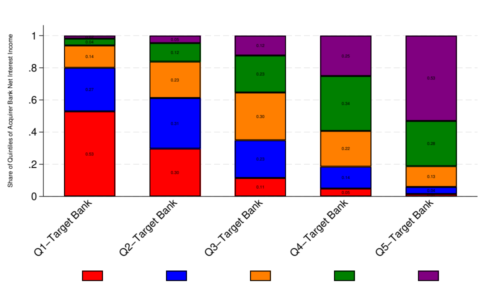
Figure 4: Assortative Matching - Quintiles of Acquirer and Target Banks



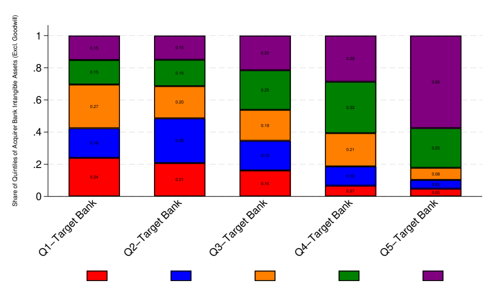
(a) Assets (Size)



(b) Net Loans



(c) Net Interest Income



(d) Intangible Assets

Note: This figure shows the share of each matched quintile of target-bank and acquirer-bank. Quintiles are constructed based on the total assets, net loans, net interest income and intangible assets within each year, respectively.

We construct quintiles based on selected bank characteristics for acquirer and target banks separately. Figure 4 documents the share of each pair of quintiles. For instance, Figure 4a indicates that within Quintile 1 of the target bank size, the share of Quintile 1 of the acquirer bank size is 52%, meaning smaller target banks are more likely to be merged with or acquired by smaller banks. Another example is Quintile 5 of target bank size, where 51% constitutes Quintile 5 of acquirer bank size, suggesting that larger acquirer banks are more likely to merge with larger target banks. This observation holds true for bank loans, net interest income, and intangible assets, as documented in Figures 4b, 4c, and 4d, respectively. In other words, acquirer banks with higher (lower) total loans, net interest income, and intangible assets are more likely to merge with target banks that have higher (lower) total loans, net interest income, and intangible assets, respectively. Therefore, we observe suggestive evidence of strong assortative matching between the two sides of M&As.

To explore the dynamics of assortative matching over time, we conduct the following regression:

$$target_{it} = \beta_{0t} + \beta_{1t} acquirer_{it} + u_t + \epsilon_{it} \tag{1}$$

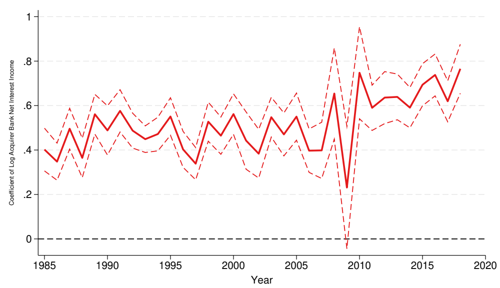
Here, the dependent variable ($target_{it}$) represents the target bank characteristics, such as the logarithm of total assets, net loans, net interest income, and intangible assets, respectively. The main independent variable ($acquirer_{it}$) denotes the acquirer bank characteristics for each corresponding variable. To account for unobserved heterogeneity, we include year (u_t) fixed effects. Our objective is to run this regression framework within each year and document the respective year-specific regression estimate of β_{1t}, indicating the time-varying degree of assortative matching between target banks and acquirer banks across different dimensions.

Figure 5 plots the regression estimate of β_{1t} over time for different selected variables of bank characteristics. In all specifications, we observe a common pattern: the estimated regression coefficient is overall positive and statistically significant throughout periods, indicating that banks with similar characteristics are more likely to engage in M&As. Additionally, we can conclude that assortative matching is a general phenomenon and is not specific to a particular time frame.

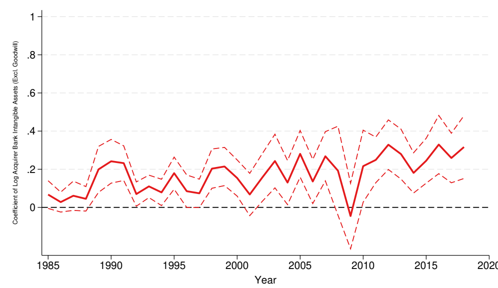
Figure 5: Assortative Matching - Regression Coefficient

(a) Assets (Size)

(b) Net Loans



(c) Net Interest Income



(d) Intangible Assets

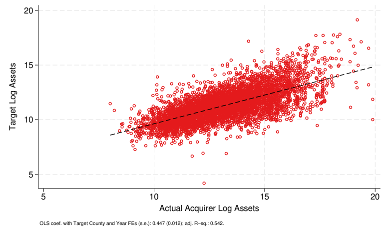
Note: This figure reports the coefficients of the logarithm of acquirer banks' interest variables for the regression of the logarithm of target banks' same interest variables over time. The regressions include year fixed effects.

3.3 Empirical Evidence on Assortative Matching in Bank M&As

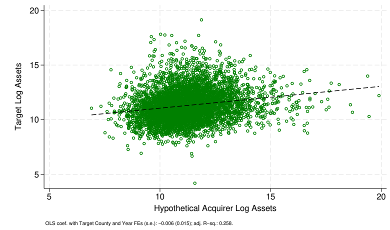
This section aims to present further empirical evidence on assortative matching between acquirer and target banks before we perform causal analysis. To do so, we construct hypothetical mergers that could have occurred but did not and compare them with actual mergers. In essence, we juxtapose actual bank mergers with randomly paired non-merging banks. For each acquirer and target bank in our sample, we substitute them with banks that did not engage in a merger within the same year. This process yields a matched sample of 5,133 pseudo-transactions, which we then compare with the actual mergers. Importantly, our methodology inherently controls for annual variations within the banking sector, as we select bank pairs from the same sector and year as the actual mergers. The critical insight of this method is that if assortative matching exists in bank

M&A transactions, random pairings of banks should not demonstrate any pattern of assortative matching, whereas actual mergers should exhibit this pattern.

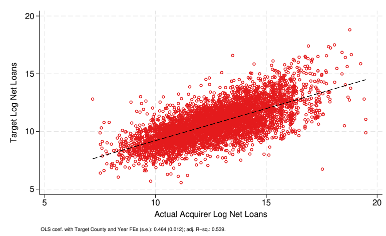
Figure 6: Actual and Hypothetical Mergers



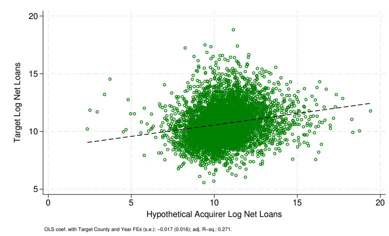
(a) Actual - Assets



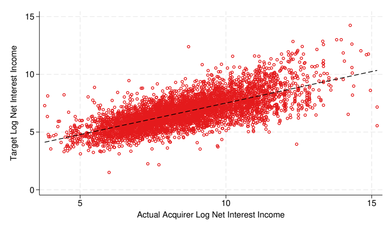
(b) Hypothetical - Assets



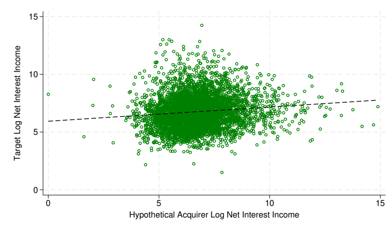
(c) Actual - Loans



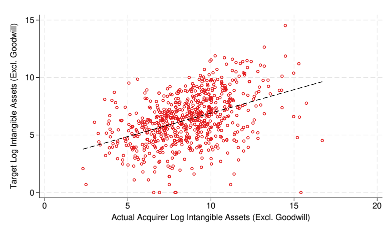
(d) Hypothetical - Loans



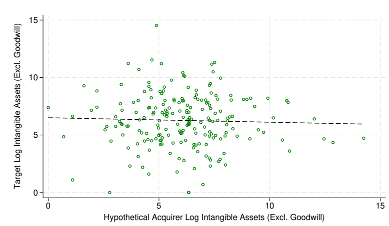
(e) Actual - Net Interest Income



(f) Hypothetical - Net Interest Income



(g) Actual - Intangible Assets



(h) Hypothetical - Intangible Assets

Note: This figure documents the scatter plot between the selected variables for both actual acquirer and target banks, as well as hypothetical acquirer and target banks. Year and target bank county fixed effects are included, and standard errors are clustered at the target bank county level.

Figure 6 illustrates the data pattern of selected metrics for both actual acquirer and target banks and hypothetical acquirer and target banks. We observe a positive and significant association between actual acquirer banks and target banks across various metrics. In contrast, there is no systematic association between hypothetical acquirers and target banks. This aligns with our expectations, as random pairings of banks are not expected to exhibit any assortative matching due to their construction, whereas real bank M&A transactions are strategically planned and sorted.

We also offer more systematic and statistical evidence supporting the presence of assortative matching, aligning with our empirical and model insights. Table 1 compares actual and hypothetical mergers using summary statistics on the actual and absolute differences of the logarithm of assets, loans, and intangible assets for acquirer-target merger pairs. The first row of each subgroup in the table reveals that hypothetical mergers exhibit a lower mean spread than actual mergers, with this difference being highly statistically significant. The second row of each subgroup explains this observation by reporting the absolute values of the acquirer-target selected metrics, which show a significant difference between actual and hypothetical merger pairs. This difference is relatively larger for actual merger pairs. Our set of findings supports the existence of assortative matching, as the random sampling method produces many more low-buy-high transactions than what is observed in the actual data.

Table 1: Spreads Between Actual and Hypothetical Mergers

	Mean Value			
Variable	Actual Mergers	Hypothetical Mergers	t(diff)	p-value
Acq. (Log Assets) - Targ. (Log Assets)	1.89	-.03	62.58	0.00
|Acq. (Log Assets) - Targ. (Log Assets)|	1.96	1.38	23.35	0.00
Acq. (Log Loans) - Targ. (Log Loans)	1.98	-.04	62.18	0.00
|Acq. (Log Loans) - Targ. (Log Loans)|	2.06	1.52	20.67	0.00
Acq. (Log NII) - Targ. (Log NII)	1.86	.001	56.57	0.00
|Acq. (Log NII) - Targ. (Log NII)|	1.93	1.42	19.84	0.00
Acq. (Log Intangible Assets) - Targ. (Log Intangible Assets)	3.38	.02	45.40	0.00
|Acq. (Log Intangible Assets) - Targ. (Log Intangible Assets|	3.84	2.01	24.34	0.00

Note: This table compares actual and hypothetical mergers using summary statistics on the actual and absolute differences of the logarithm of assets, loans, and intangible assets for acquirer-target merger pairs. Hypothetical mergers are randomly constructed within each year to capture bank mergers that could have happened but did not.

We also conduct a Probit analysis to determine the probability of being an actual merger based on selected acquirer-target metrics (loans, net interest income, and intangible assets), while controlling for size differences. The objective is to explore whether absolute differences in merger pairs could account for the probability of an actual merger and, if so, in which direction. Therefore, the crucial test of our regression model involves examining the coefficient of the merger dummy on the selected merger metrics. As shown in Table 2, the coefficient in each regression specification is consistently negative and highly statistically significant. This finding suggests that the "like-buys-like" effect is notably stronger in actual mergers than it would be if we paired non-merging banks during the same periods. In other words, as acquirer and target banks have more similar levels of loans, net interest income, and intangible assets, they are more likely to engage in M&A transactions. Consequently, our analysis confirms the presence of assortative matching between acquirer and target banks.

Table 2: Probit Estimates - Actual and Hypothetical Mergers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
|Acq. (Log Loans) - Targ. (Log Loans)|	-0.280***	-0.301***					-0.401
	(0.0289)	(0.0296)					(0.420)
|Acq. (Log NII) - Targ. (Log NII)|			-0.345***	-0.368***			-0.532
			(0.0341)	(0.0362)			(0.429)
|Acq. (Log Intangible Assets) - Targ. (Log Intangible Assets)|					-0.124***	-0.196***	-0.167**
					(0.0372)	(0.0445)	(0.0614)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	Yes
Target County FE	No	Yes	No	Yes	No	Yes	Yes
Observation	7719	7719	6770	6768	678	583	583

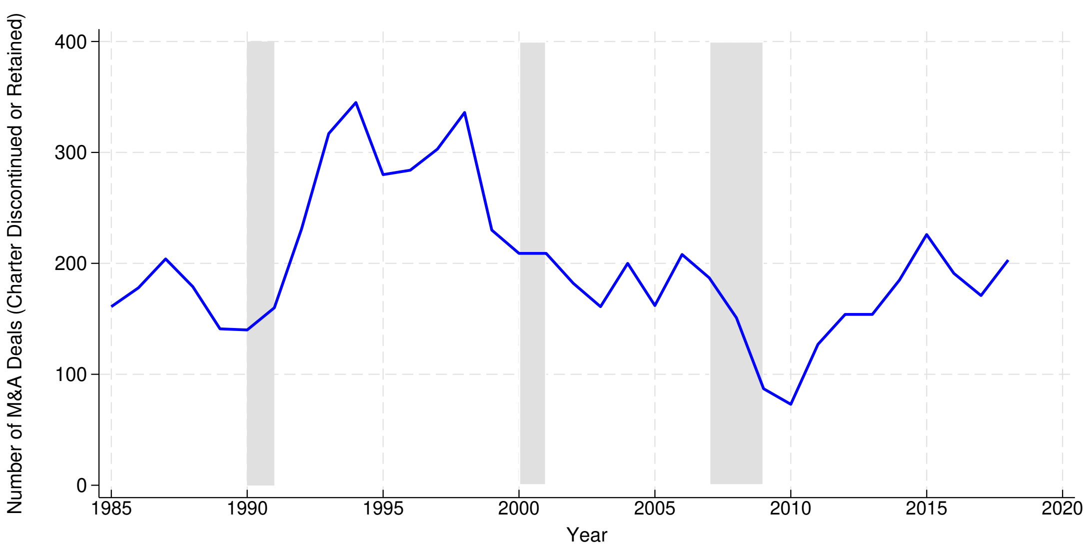
Note: This table presents the Probit regression estimates for the dependent variable as 1 if the observation is an actual merger, zero otherwise (i.e. hypothetical merger). Explanatory variables are absolute differences of i) logarithm of loans, ii) logarithm of net interest income (NII), and iii) logarithm of intangible assets in merger pairs. Control variables are acquirer and target banks logarithm of total assets. Standard errors (in parentheses) are clustered at the target bank county-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.4 Cyclicality of Bank M&As and Assortative Matching

One potential explanation for the dynamics in bank M&As and assortative matching is that the aggregate economic environment, such as recession or boom periods, affects the incentives for bank consolidations. As a related note, Granja et al. (2017) argues that the dimensions and characteristics of acquirer-target banks dramatically alter during the Great Recession period if we consider failed target banks.Although our paper focuses solely on traditional M&As classified as "*Charter Discontinued*" and "*Charter Retained*", the overall economic environment would still exhibit a cyclical pattern over time. As a result, our mechanism may be influenced by broader economic conditions or cycles. To address this channel, we investigate whether our results are invariant to the general economic conditions in different periods. We examine the cyclicality of bank M&A activity and assortative matching to ensure that our baseline evidence and insights are robust and not a period-specific phenomenon.

First of all, Figure 7 shows the total number of M&A deals (either charter discontinued or retained) over time, highlighting the NBER recession periods. We observe that the number of M&A deals declines only during the last two recession periods (the 2001 IT bust and the 2007-2009 financial crisis), whereas it does not exhibit a declining pattern during the recession period 1990-1991.

Figure 7: Number of M&A Deals (Charter Discontinued or Charter Retained)



Note: This figure shows the total number of M&A deals (either charter discontinued or retained) over time by highlighting the NBER recession periods.

To provide more systematic evidence, we perform a Probit regression of a dummy variable for M&A transactions on a dummy variable for recession periods, controlling for the acquirer-level logarithm of total assets, deposits, loans, and equity. Table 3 shows that M&A deals are less likely to occur during recession periods, which is intuitive, as higher uncertainty and risk might inhibit the incentives for bank consolidations. However, we do not find a statistically significant association when we include year and/or acquirer bank county fixed effects. In other words, the results imply no systematic relationship between the state of the economy and M&A decisions.

Even though we find that recession periods do not systematically influence M&A decisions, this result pertains more to the extensive margin of M&A deals. However, our baseline findings primarily concern the intensive margin of M&A deals, specifically related to assortative matching. In other words, once banks decide to engage in M&A transactions, how do the sorting mechanisms work? Does the cyclical behavior of the economy impact sorting and assortative matching?

Table 3: Probit Regression - M&A vs. Recession

	M&A	M&A	M&A	M&A
Recession	-0.145***	-0.0945***	-0.0589	-0.0565
	(0.0129)	(0.0137)	(0.0935)	(0.0919)
Control Variables	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Acquirer County FE	No	No	No	Yes
Observation	1732383	1725335	1725335	1687681

Note: This table presents the Probit regression estimates for the dependent variable, which is 1 if the observation is a merger and 0 otherwise. The main explanatory variable of interest is a dummy variable for recession periods, which is 1 if the year corresponds to the NBER recession periods in our sample (1975, 1980-1982, 1990-1991, 2001, 2007-2009) and 0 otherwise. Control variables are the acquirer-level logarithms of total assets, equity, deposits, and loans. Standard errors (in parentheses) are clustered at the acquirer bank county-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To test this question, following our previous insights, we regress our proxy empirical measures of assortative matching (absolute differences of i) logarithm of loans, ii) logarithm of net interest income (NII), and iii) logarithm of intangible assets in merger pairs on a dummy variable for recession periods, controlling for the acquirer-level and target-level logarithms of total assets. Table 4 indicates that the dummy variable for recession periods is insignificant in explaining the assortative matching measures. This suggests that recession periods do not appear to be an important factor behind our baseline findings. In this respect, we can argue that our results on assortative matching are robust with respect to the cyclical behavior of the aggregate economy. Hence, assortative matching in bank M&A transactions appears to be a general phenomenon rather than a time-specific pattern.

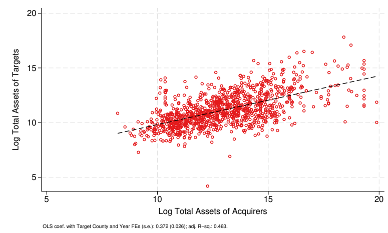
Table 4: Assortative Matching vs. Recession

	(1)	(2)	(3)
	|Log Loans|	|Log NII|	|Log Intangible Assets|
Recession	-0.0381	0.0421	-0.983
	(0.0332)	(0.0423)	(0.682)
Control Variables	Yes	Yes	Yes
Acquirer Bank FE	Yes	Yes	Yes
Target County FE	Yes	Yes	Yes
R^2	0.944	0.958	0.791
Observation	2456	2120	242

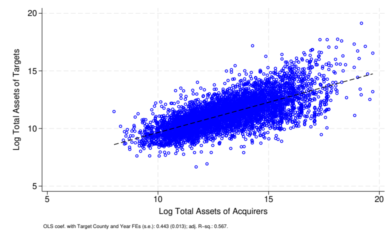
Note: Dependent variables are absolute differences of i) logarithm of loans, ii) logarithm of net interest income (NII), and iii) logarithm of intangible assets in merger pairs, which are our proxies of the degree of assortative matching. The main explanatory variable of interest is a dummy variable for recession periods, which is 1 if the year corresponds to the NBER recession periods in our sample (1975, 1980-1982, 1990-1991, 2001, 2007-2009) and 0 otherwise. Control variables are the acquirer-level and target-level log of total assets. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We also provide visual evidence showing that recession periods are not an important factor in explaining the assortative matching pattern in bank M&A transactions. Figure 8 presents scatter plots of the selected variables for both actual acquirer and target banks, separately for recession and non-recession periods. We observe that the underlying associations in the scatter plots exhibit similar patterns for both recession and non-recession periods. Therefore, once again, we do not find strong and significant evidence that the cyclical pattern of the aggregate economy plays a key role in explaining assortative matching in bank M&A transactions.

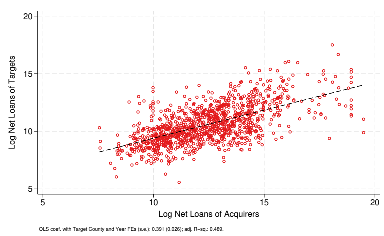
Figure 8: Assortative Matching - Recession and Other Periods



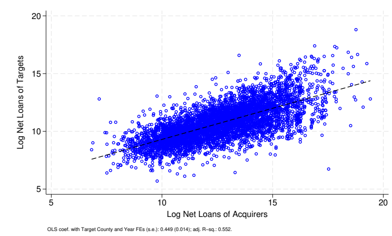
(a) Assets - Recession Per.



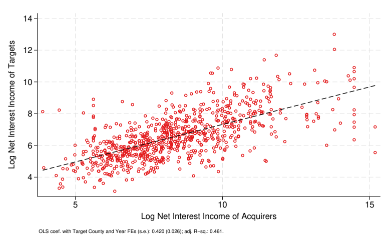
(b) Assets - Other Per.



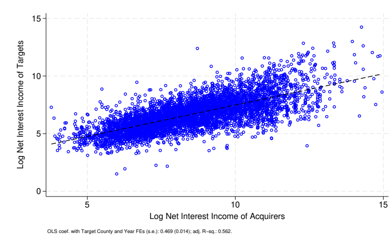
(c) Loans - Recession Per.



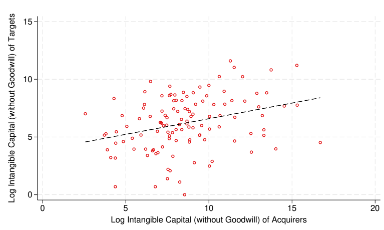
(d) Loans - Other Per.



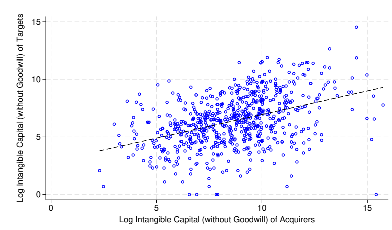
(e) NII - Recession Per.



(f) NII - Other Per.



(g) Intangible Assets - Recession Per.



(h) Intangible Assets - Other Per.

Note: This figure documents the scatter plot between the selected variables for acquirer banks and acquiree/target banks in terms of the (i) logarithm of total assets, (ii) logarithm of total loans, (iii) logarithm of net interest income, and (d) logarithm of intangible assets, separately for recession and non-recession periods. Year and target bank county fixed effects are included, and standard errors are clustered at the target bank county level.

4 Causal Analysis

Given that we documented some stylized facts regarding the role of intangible assets and assortative matching in bank M&As, our next goal is to provide causal effects of bank M&As on bank loan and operating efficiency performance through the channel of intangible asset synergies.

Identification Strategy A key challenge for causal identification is the potential selection bias of acquirers and targets in bank M&As, which could be endogenous to the dependent variable, annual loan growth. To address these endogeneity concerns, we adopt a quasi-natural experimental approach commonly used in the literature (e.g., Seru (2014), Bena and Li (2014), Li et al. (2018), Masulis et al. (2023)). Specifically, we focus on terminated and withdrawn bank M&As that failed due to reasons unrelated to bank performance and/or intangible assets targeted in such deals. Consequently, our identification strategy estimates the impact of intangible asset synergy in M&As on acquirer loan growth and improvements in operating efficiency by comparing successful acquirers to a control group of comparable acquirers whose M&As did not proceed due to exogenous factors.

To make sure deals are terminated or withdrawn due to unrelated reasons, we first examine the deal summaries of terminated and withdrawn bank M&As provided by S&P Global - Capital IQ and SDC Platinum and remove any deals that reference the performance and/or intangible assets of the target or acquirer banks. Second, we crosscheck using the Capital IQ - Key Events database which provides additional details for company news and includes categories such as M&A Rumors, M&A Cancellations, and M&A Completions. Third, we examine Federal Reserve press releases "Actions of the Board, Its Staff, and the Federal Reserve Banks - H.2" which includes approved and withdrawn bank M&A applications since 1996.[1] A letter[2] from the Fed chair Jerome Powell to senator Elizabeth Warren on May 10, 2018 shed more light on withdrawn bank M&As. Powell explains that most applications are withdrawn due to expected regulatory objections.

[1]The releases can be found at here, and prior releases can be found at fraser.stlouisfed.org

[2]The letter can be found here.

Lastly, we manually search for news about these terminated or withdrawn deals. To give an example of how we manually check the news, below is a passage that we found in the Los Angeles Times[3] regarding the terminated deal between acquirer bank CommerceBancorp and target bank Michigan National Corporation in 1992. The passage notes that 'several business loans went bad and construction loans soured with the continuing recession in the real estate market (highlighted in red in the passage)' for the acquirer bank one year before the deal. We drop this deal from the sample because it was likely to be terminated due to reasons related to bank performance.

> *"I would have liked to have seen the deal go forward," said Raymond E. Dellerba, CommerceBancorp's president and chief executive. "I don't know if the economy scared them away or what. They're a very fine organization, like we are." The holding company for CommerceBank in Newport Beach had been one of Orange County's bigger and better-run banks through most of the 1980s. But it sank into red ink last year as several business loans went bad and construction loans soured with the continuing recession in the real estate market. Dellerba said the bank had to foreclose on a number of construction projects, raising the amount of troubled real estate it owned from $6.3 million in the first quarter this year to $17.1 million at the end of June. Recent and pending sales of some of those projects should reduce the amount "substantially," he said."*

We apply this manual check to all the terminated deals in our sample and drop those for which we can identify mentions of bank performance and intangible assets that may have contributed to the termination, as illustrated in the passage above. This approach provides a sample of terminated or withdrawn deals that failed due to reasons unrelated to the performance or intangible assets of involved parties. Consequently, our control group consists of comparable acquirer banks whose terminated or withdrawn M&As are not influenced by our key variable of interest, intangible asset synergy.

Moreover, for our DiD analysis to yield valid results, there must be sufficient overlap in key covariates between the treated and control groups to ensure that both groups are

[3] The full article can be found here.

comparable regarding observable characteristics, such as bank size, deposits, and equity. To address this, we match the acquirer banks in the treated group with those in the control group based on assets, loans, equity, and operating efficiency using the propensity score reweighting estimator model. As a result, in the final sample for the DiD analysis, we obtained comparable bank characteristics across both groups.

Identification Assumptions In conducting a difference-in-differences (DiD) analysis to examine the role of intangible asset synergy in post-merger performance, we have several key identification assumptions. First, the treated and control groups would have exhibited similar trends in the outcome variable—annual loan growth and operating efficiency growth—during the pre-merger period without treatment. Therefore, the assumption is that the loan growth and operating efficiency growth trends between these two groups were parallel before the M&A event. This assumption ensures that any post-merger differences in loan growth and operating efficiency growth can be attributed to the success of the merger rather than pre-existing differences between the two groups. Second, we assume that banks in the treated group did not alter their behavior in anticipation of the success or failure of the M&A deal before the merger took place. Specifically, it is assumed that the annual loan growth and operating efficiency growth of acquirer banks were not influenced by expectations about whether the deal would eventually be completed or withdrawn. Third, we assume that there were no significant events or shocks (e.g., macroeconomic events, regulatory changes, or industry-wide shifts) that systematically affected either the treated or control group but not the other during the study period.

Sample Selection and Measures We apply several sampling procedures to robustly define the treated and control groups in our DiD causal inference. First, since the unit of observation in terminated and withdrawn M&A deals is primarily at the bank-holding company level, we also measure our key variables of interest at this level in completed (successful) M&A deals. Second, to avoid instances where acquirer banks might be classified as treated or control in subsequent or multiple years, we limit our sample to bank-holding company acquirers that engage in only one M&A deal during the entire sample period, ensuring that each bank-holding company is classified as treated or control only once. Third, we exclude bank-holding companies that appear in both completed and terminated/withdrawn M&A deals to ensure that each bank-holding company is assigned exclusively to either the treatment or control group, but not both. Finally, we restrict our analysis to the five years before and after the M&A deal to ensure that the treated and control group acquirer banks have a balanced panel.

A potential concern in our comparison between the treated and control groups is that our key variable of interest could mechanically increase for the treated group due to the nature of bank consolidations through M&A deals, independent of the channel of intangible synergy. To address this valid concern, we follow the methodology outlined by Dell'Ariccia and Garibaldi (2005) and eliminate the mechanical increase in our key variables. First, we compute the quarter-to-quarter net change in our variables of interest (assets, loans, deposits, and equity) for the acquirer banks in the treated group and subtract the corresponding values from one quarter prior to the M&A event for the target banks. To robustly measure the net changes, we exclude bank holding companies from our sample if they have missing values for their target banks' corresponding Call Reports variables one quarter prior to the M&A event. This adjusted difference alleviates concerns about mechanical increases in variables due to bank consolidations.

As a result of our sampling procedures for the causal analysis, the final sample includes 211 unique acquirer bank holding companies in the treated group and 62 unique acquirer bank holding companies in the control group, totaling 3,549 bank-year observations.

Causal Framework We explore the heterogeneous dynamic responses of acquirer banks that exhibit varying degrees of assortative matching in intangible assets. This investigation is crucial for understanding how the alignment of intangible assets between acquirer and target banks dynamically influences the effects of mergers and acquisitions (M&A). To this end, we employ a dynamic Difference-in-Differences (DiD) framework coupled with an event study approach, which enables us to capture both the immediate and long-term effects of the treatment on bank performance, particularly in terms of annual loan growth and annual growth in operating efficiency, based on the following framework:

$$Y_{it} = \sum_{k=-5}^{+5} \beta_k (\mathbb{1}\{\text{k Years to M\&A}\} \times \text{Treat}_i) + \Gamma X_{it} + \eta_i + \varepsilon_t + \phi_{ic} + \epsilon_{it} \tag{2}$$

where the subscripts i, t index the acquirer bank-holding company and the year, respectively. The dependent variables are (i) annual loan growth, and (ii) annual growth in operating efficiency (operating income per non-interest expense). $\mathbb{1}\{\text{k Years to M\&A}\}$ is an indicator function that takes the value of 1 if the difference between a particular year and the year of the M&A deal is k, with $k \in [-5, 5]$. Treat_i is a dummy variable indicating whether a particular bank-holding company engaged in successful or withdrawn/terminated M&A deals (1 for successful M&A deals, 0 otherwise). X_{it} represents bank-holding company-level control variables, including the logarithms of assets, deposits, equity, and operating efficiency when the dependent variable is annual loan growth, and the logarithms of assets, loans, and equity when the dependent variable is annual growth in operating efficiency. We also include acquirer bank (η_i), year (ε_t) and acquirer bank county (ϕ_{ic}) fixed effects to account for unobserved heterogeneity. Our coefficient of interest is β_k, which represents the causal impact of bank M&A on annual loan growth. We cluster the standard errors at the bank-holding company level and interpret our estimates at the 90% confidence interval.

Causal Estimates Figure 9 illustrates the dynamic causal impact of bank M&As on annual loan growth and annual growth in operating efficiency. To distinguish the role of intangible asset synergies in the causal estimates, we construct two bins within the treated group: one for acquirer banks with higher assortative matching (above the median) in terms of intangible assets during the M&A deal, and another for acquirer banks with lower assortative matching (below the median). In this classification, as discussed in the empirical facts, we define assortative matching based on the absolute difference in intangible assets between acquirer and target banks; the smaller the difference, the higher the assortative matching.

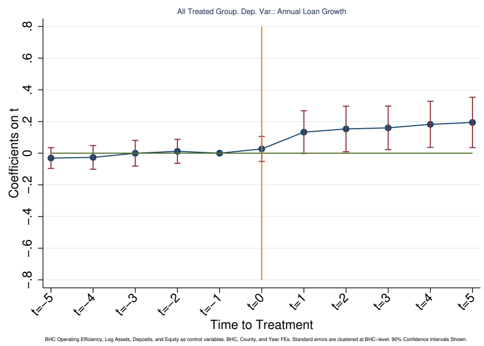
First, in Figures 9a and 9b, which include all treated groups, we observe relatively stable pre-trends across all panels, supporting the validity of the parallel trends assumption. Second, the panel representing the entire treated group shows a noticeable upward trend in the coefficients during the post-treatment period, suggesting a significant positive effect of the treatment on annual loan growth and annual growth in operating efficiency. In terms of magnitude, we find that the treated group experienced an increase in annual loan growth of approximately 2 percentage points and an increase in annual growth in operating efficiency of around 1 percentage point per year during the post-merger periods compared to the control group. This upward trajectory indicates that the treatment effectively enhanced the banks' lending capacities and operating efficiency.

In the panel with treated acquirers that have higher assortative matching in intangible assets (Figures 9c and 9d), the observed pattern mirrors that of the overall graph but demonstrates more pronounced effects. In this subgroup, the positive and significant effects on loan growth and operating efficiency growth are much higher compared to the previous graphs. This indicates that banks with higher assortative matching in intangible assets experienced a more substantial increase in loan growth and operating efficiency growth post-treatment. The results suggest that the synergies derived from successful M&As are more effectively realized in this group, reinforcing the notion that the assortative matching in bank M&A transactions plays a critical role in post-merger performance.

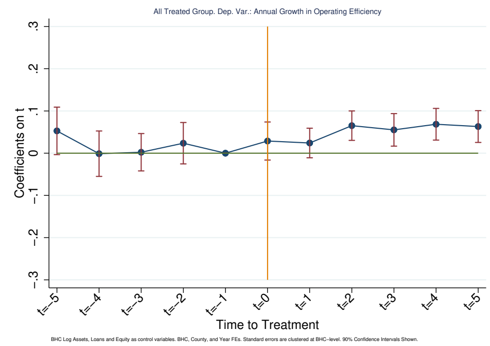
Lastly, in the panel with treated acquirers that have lower assortative matching in intangible assets (Figures 9e and 9f), although it shows a positive trend in annual loan growth and annual growth in operating efficiency after treatment, the effect is less pronounced than that observed in the higher assortative matching group and is also statistically insignificant. The relatively modest and statistically insignificant increase in loan growth indicates that banks in this category did benefit from the treatment but to a lesser extent than their higher assortative matching counterparts.

Therefore, our analysis reveals that the treatment had a positive impact on both annual loan growth and annual growth in operating efficiency, particularly pronounced among banks with higher assortative matching in intangible assets. This finding highlights the critical role of intangible asset synergies in enhancing post-merger performance.

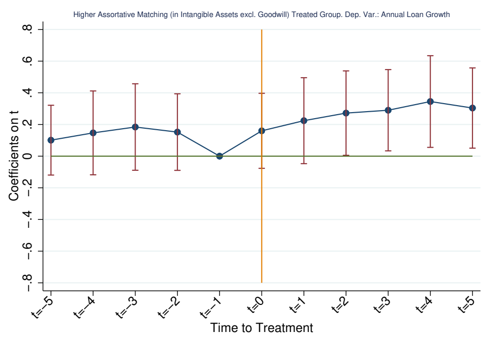
Figure 9: Dynamic DiD - Annual Growths in Loan and Operating Efficiency



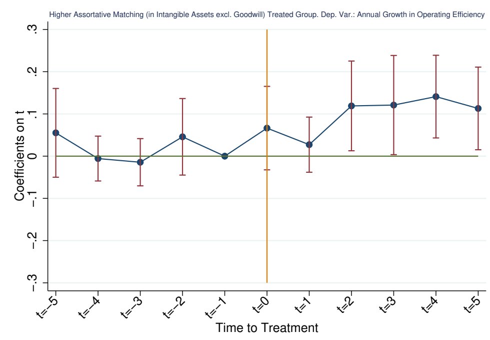
(a) Loan Growth - All



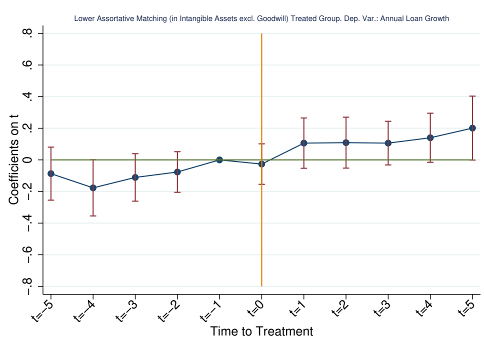
(b) Operating Eff. Growth - All



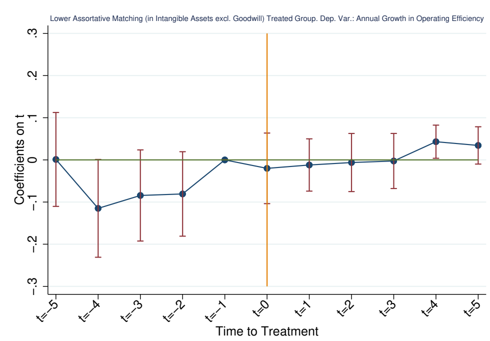
(c) Loan Growth - Higher Assortative



(d) Operating Eff. Growth - Higher Assortative



(e) Loan Growth - Lower Assortative



(f) Operating Eff. Growth - Lower Assortative

Note: This figure presents the dynamic difference-in-differences estimates of the regression model outlined in equation (2). We categorize the acquirer banks within the treated group into two categories: acquirer banks with higher assortative matching (above the median) in terms of intangible assets during the M&A deal, and acquirer banks with lower assortative matching (below the median). The regression model includes bank holding company-level control variables (the logarithms of total assets, loans, and equity, along with operating efficiency when the dependent variable is annual loan growth), as well as year, acquirer bank, and acquirer bank county fixed effects. Standard errors are clustered at the bank holding company level, and confidence intervals are calculated at the 90% level.

5 Model

In the spirit of Rhodes-Kropf and Robinson (2008), we adapt their model of a continuous time version of a Diamond-Mortensen-Pissarides search model to examine the market of mergers and acquisitions amongst banks. We take a simplified view that intangible asset stock determines a bank's total loans in the lending market while simultaneously raising the monitoring/screening costs nonlinearly. We focus on the complementarity and substitutability of intangible assets and the assortative matching that can occur when bank consolidations are possible. When synergy benefits exhibit complementarity, we expect bank consolidation patterns to reflect a natural pairing across similar banks. While under substitutability, we expect pairings to reflect a divergence in similarity.

A striking feature of the model is that, although the search environment is assumed to be random, once the acquirer and acquiree meet after the search, they endogenously decide to approve or reject the deal based on various factors, such as the degree of intangible asset synergies and the substitutability or complementarity between the two agents. Consequently, assortative matching in equilibrium becomes an endogenous outcome. Another motivation for our model is to deliver propositions regarding the conditions under which assortative matching occurs pre-merger and how intangible asset synergies affect post-merger performances.

Our key motivations for developing a theoretical model are twofold. First, although our empirical section provides a causal analysis of the relationship between intangible asset synergy, assortative matching, and post-merger bank performance, it is still a reduced-form analysis. Our model framework can characterize the conditions under which assortative matching occurs and how it leads to post-merger efficiency, helping us understand the underlying environment of our empirical results. Second, our empirical analysis, by its nature, cannot conduct any counterfactual analyses. We use our theoretical framework as a laboratory to provide counterfactual analyses to see how the degree of merger regulations impacts the likelihood of assortative matching and post-merger efficiency.

5.1 Setup

There are two markets[4], denoted $i \in A, B$, each containing a continuum of entrepreneurs endowed with an ex-ante profitable project that requires a capital inflow of \$1 but has no private resources. So, they must seek a bank to obtain financing. A project's payoff is R with probability θ and 0 with probability $1 - \theta$ with $R\theta > 1$. We assume that payoffs between entrepreneurs and banks are perfectly observable and contractible. Within these two markets are two types of banks denoted by $j \in s, l$, with both having access to an unlimited supply of funds at a constant gross interest rate normalized to one. Each financial intermediary has market-specific intangible assets $N_{i,j}$ that can be redeployed to another market once a merger occurs. The cost of one unit of intangible assets is also assumed to cost \$1 and can be instantaneously adjusted with no friction.[5] Thus, intangible asset stock is always optimal and maximizes the bank's value at all times. The types $j \in s, l$ of financial intermediaries vary by a parameter $\phi_{i,j} > 1$. This parameter can represent managerial talents or other intrinsic characteristics not captured by intangible assets but which affect lending activities. In equilibrium, banks with differing utilization rates will invest different amounts of intangible assets. We have four different types of financial intermediaries in the model as $(\phi_{A,s}, N_{A,s}),\ (\phi_{A,l}, N_{A,l}),\ (\phi_{B,s}, N_{B,s}),\ (\phi_{B,l}, N_{B,l})$. We remark that a rise in the utilization rate corresponds with a rise in the value of a bank.

For market, $i \in A, B$, and financial intermediary $j \in s, l$, an increase in intangible asset expands its issuance of loans with a constant scale of returns. We model as

$$m_{i,j}(\cdot) = \phi_{i,j} N_{i,j}, \qquad 0 \leq N_{i,j} \leq \overline{N}$$

where $\phi_{i,j} > 1$ and $0 < \beta < 1$. Intangible asset stock is bounded by $\overline{N}$, and the mass of financial intermediaries M_j in market j is assumed to be bounded strictly less than the mass of the market. These two assumptions ensure no strategic interactions among competitors occur and that aggregate market shares in each market remain sensible. $\overline{N}$ is assumed to

[4]The intuition behind having two markets is to highlight market-specific intangible assets such as mortgage servicing rights, purchased credit card portfolios, and core deposit intangibles. Acquiring these assets can lead to intangible asset synergies.

[5]The required rate of return is given as $r \in (0, 1)$.

be sufficiently small such that in the optimum, there is a measure of entrepreneurs in both markets who do not have access to a bank. Each financial intermediary can only finance projects within their market A or B. This incentivizes financial intermediaries to invest or acquire intangible assets through a merger/acquisition. Each financial intermediary also incurs monitoring/screening cost

$$C_{i,j}(\cdot) = (N_{i,j})^{\alpha}$$

with $\alpha > 1$. The cost function ensures an interior solution for intangible assets. We allow instantaneous and frictionless adjustment of the intangible asset stock.

Each financial intermediary can also choose to merge.[6] If two financial intermediaries in each market of type $j, j' \in s, l$ merge, then the new entity possesses a utilization parameter that is a function of pre-merger utilization parameters, that is $\phi_M(\phi_{A,j}, \phi_{B,j'})$. The loan issuance for a merged financial intermediary becomes

$$m^M_{A_j,B_{j'}} = \phi_M(\phi_{A,j}, \phi_{B,j'})\{N_{A,j} + N_{B,j'}\}, \qquad 0 \leq N_{A,j}, N_{B,j'} \leq \overline{N}.$$

For a merged financial intermediary, we take the consolidated view on monitoring/screening costs,

$$C^M_{A_j,B_{j'}}(N_{A,j}, N_{B,j'}) = (N_{A,j})^{\psi} + (N_{B,j'})^{\psi}$$

where $\psi > 1$. We assume permanent changes in cost structure where ψ can be related to the adjustment costs associated with the redeployability of intangible assets of the merged financial intermediary across both markets. For an exogenous stock of intangible assets $N_{A,j}$ and $N_{B,j'}$ depending on relation between α and ψ we could have

$$\begin{cases} C^M_{A_j,B_{j'}}(N_{A,j}, N_{B,j'}) > C_{A,j}(N_{A,j}) + C_{B,j'}(N_{B,j'}). & \text{if } \psi > \alpha \\ C^M_{A_j,B_{j'}}(N_{A,j}, N_{B,j'}) = C_{A,j}(N_{A,j}) + C_{B,j'}(N_{B,j'}) & \text{if } \psi = \alpha \\ C^M_{A_j,B_{j'}}(N_{A,j}, N_{B,j'}) < C_{A,j}(N_{A,j}) + C_{B,j'}(N_{B,j'}) & \text{if } \psi < \alpha. \end{cases}$$

Monitoring/screening costs may not necessarily decline for the merged financial intermediary. It highlights in partial equilibrium that diseconomies of scale in monitoring/screening costs may persist post-merger.

[6] We use the terms merger and acquisition synonymously within the model.

To highlight the possible gains in a merger, we first consider a static setting where a financial intermediary optimally chooses intangible asset stock. The financial intermediary would choose investments that equalize the marginal benefits accounting for marginal monitoring/screening costs. For simplicity, we assume intangible assets do not depreciate. The optimal bank's value for type j in market i is

$$\Pi_{i,j} = m_{i,j}(N_{i,j})(\theta R - 1) - C_{i,j}(N_{i,j}).$$

Thus, a merger is profitable when

$$\begin{aligned}\Pi_{A,j} + \Pi_{B,j'} \leq \Pi^M_{A_j,B_{j'}} \equiv & \phi_M(\phi_{A,j}, \phi_{B,j'})\{N^*_{A,j} + N^*_{B,j'}\}(\theta R - 1) - (N^*_{A,j})^\psi + (N^*_{B,j'})^\psi \\ & - r\{N^*_{A,j} + N^*_{B,j} - N_{A,j} - N_{B,j}\},\end{aligned}$$

$N^*_{A,j},\ N^*_{B,j'}$ is the optimal intangible asset stock if a merger occurs. If mergers and acquisitions among financial intermediaries were motivated by substitutability, the higher utilization of the combined resources of the merged bank would raise the merged bank's value. This reasoning remains consistent with the findings by Focarelli et al. (2002), which provides empirical support that bank acquisitions in Italy were primarily driven to restructure the loan portfolio of the acquired bank. We assume the same functional form assumption as in Rhodes-Kropf and Robinson (2008) to model substitutability, that is, $\phi_M = \max\{\phi_{A,j}, \phi_{B,j'}\}$. If mergers and acquisitions among banks were motivated by complementarity, then banks of similar characteristics (i.e., size, geographic, and lending specialties) would be better off consolidating their organizations. As remarked by Topkis (1998) and Shimer and Smith (2000), complementarity would suggest a supermodularity condition related to the value of matched consolidated banks. We arrive at a similar inequality,

$$\Pi^M_{A_l,B_l} + \Pi^M_{A_s,B_s} \geq \Pi^M_{A_l,B_s} + \Pi^M_{A_s,B_l}.$$

Note that the inequality would be reversed if substitutability was the motivation. We model the functional form for complementarity as the multiplicative, $\phi_M(\phi_{A,j}, \phi_{B,j'}) = \phi_{A,j} \cdot \phi_{B,j'}$ where $\phi_{A,j}, \phi_{B,j'} > 1$.

5.2 Stochastic Nature

There are two states of nature, the No-Merger state (NM) and the Mergers are Possible State (MP), denoted by $\Sigma \in \{\Sigma^{NM}, \Sigma^{MP}\}$ and associated with state intensities $\lambda \in \{\lambda^{NM}, \lambda^{MP}\}$. The probability of remaining in state Σ over the next time interval Δ is $e^{-\Delta\lambda^{\Sigma}}$. In the NM state, there are no profitable merger opportunities, $\phi_{A,j} > \phi_M(\phi_{A,j}, \phi_{B,j'})$ for all types j, j' in both markets. If the economy is in the Σ^{NM} state, there is a probability $1 - e^{-\Delta\lambda^{NM}}$ that a positive shock occurs to $\phi_M(\cdot,\cdot)$. The state switches to Σ^{MP} if the shock is realized and profitable merger opportunities are available.

In the model, banks do not merge before the shock in anticipation of synergy benefits. The nature of the shock can be imagined to represent unknown discoveries that lead to synergy benefits ex-post. In the MP state, we assume the parameters of interest are consistent, so mergers are mutually profitable. When the shock occurs, we assume it is common knowledge for all banks. The ability to contract the synergy benefits from the complementarity of assets is precluded because of the incomplete contracting and hold-up problem. Synergy benefits can only be obtained by placing the intangible assets under common control. If a bank remains a stand-alone entity and invests in more intangible assets, then $\phi_{i,j}$ remains the same as before the shock. The intuition is these synergy benefits arise because banks may invest in different types of intangible assets.

Let $\Pi^{NM}_{i,j}$ represent the present value of a type j bank in market i in the NM state and $\Pi^{MP}_{i,j}$ represent the present value in the MP state before it has located a potential partner. If a type j bank in market i finds a potential partner type j' bank in market i', both parties engage in Nash bargaining. If a deal is struck, let $\Pi^{M}_{i_j,i'_{j'}}$ represent the expected value of the merger to the type j bank who mergers with the type j' bank. If a deal is not reached, then the banks continue to search for another potential partner with their value remaining at $\Pi^{MP}_{i,j}$, to which at any time the state may return to the NM state with value $\Pi^{NM}_{i,j}$.

5.3 Optimality in Each State

The world begins in the NM state. Each type j bank in market i chooses its intangible asset investment $I_{i,j}$ to maximize the discounted value of the bank, which is the sum of assets and net gains from lending less investment costs:

$$\max_{I_{i,j}} \left\{ \left(N_{i,j} + I_{i,j} + \Delta\phi_{i,j}\left(N_{i,j} + I_{i,j}\right)(\theta R - 1) - \Delta\{N_{i,j} + I_{i,j}\}^{\alpha}\right) e^{-r\Delta} - I_{i,j} \right\},$$

where i denotes market and j denotes the bank type. The asset stock always satisfies the optimum in the NM state of the following:

$$N_{i,j}^{NM^*} = \left[\frac{\phi_{i,j}(\theta R - 1) - r}{\alpha}\right]^{\frac{1}{\alpha-1}}$$

Over this Δ time interval, a shock may occur or not let $\Pi_{i,j}^{NM}$ represent the expected value of the NM state and $\Pi_{i,j}^{MP}$ represent the expected value of the MP state. In the NM state, the expected value of a type j bank is simply the weighted average of each future state plus interim lending profits. We have,

$$\Pi_{i,j}^{NM} = \left[e^{-\Delta\lambda^{NM}}\Pi_{i,j}^{NM} + (1 - e^{-\Delta\lambda^{NM}})\Pi_{i,j}^{MP} + \Delta\left(\phi_{i,j}N_{i,j}^{NM^*}(\theta R - 1) - \left(N_{i,j}^{NM^*}\right)^{\alpha}\right)\right] e^{-r\Delta}.$$

After a merger between a type j bank in market A and type j' bank in market B, the consolidated bank chooses its intangible asset stock to maximize

$$\begin{aligned}\max_{-N_{A,j}^{NM^*} \le I_A;\ -N_{B,j'}^{NM^*} \le I_B} \Bigg[&\Delta\Big\{\phi_M(N_{A,j}^{NM^*} + I_A + N_{B,j'}^{NM^*} + I_B)(\theta R - 1) \\ &- (N_{A,j}^{NM^*} + I_A)^{\psi} - (N_{B,j'}^{NM^*} + I_B)^{\psi}\Big\}e^{-r\Delta} \\ &- \max\{I_A + I_B, 0\} + (N_{A,j}^{NM^*} + N_{B,j'}^{NM^*} + I_A + I_B)e^{-r\Delta}\Bigg].\end{aligned}$$

The optimal intangible assets for each market $i \in A, B$ is

$$N_i^{M^*} = \left[\frac{\phi_M(\theta R - 1) - r}{\psi}\right]^{\frac{1}{\psi-1}}.$$

We make the following assumption to ensure the consolidated bank's optimal intangible asset stock exceeds a standalone bank's.

Assumption 5.1 *For a type j bank in market i and a type j' bank in market i' the synergy benefits* *of a merger exceed a lower bound given by the inequality*

$$\phi_M > \frac{r}{\theta R - 1} + \frac{\psi}{\theta R - 1} \max\left\{ \left[\frac{\phi_{i,j}(\theta R - 1) - r}{\alpha}\right]^{\frac{\psi-1}{\alpha-1}}, \left[\frac{\phi_{i',j'}(\theta R - 1) - r}{\alpha}\right]^{\frac{\psi-1}{\alpha-1}} \right\}.$$

Assumption 5.1 says the synergy benefits of a would-be consolidated bank exceed any additional operating costs.

We assume consolidated banks face no external shocks in the periods after the merger. Thus, the intangible asset stock remains the same for all future periods. The value of the consolidated bank is simply the discounted profits from lending activities:

$$\frac{\phi_M(N_A^{M^*} + N_B^{M^*})(\theta R - 1) - (N_A^{M^*})^{\psi} - (N_B^{M^*})^{\psi}}{r}.$$

If a type j bank in market A matches with a type j' bank in market B before a merger occurs, both banks negotiate how to split the expected surplus. We model this negotiation process as a Nash bargaining solution. The expected value of the consolidated bank is the discounted profits from lending activities, less the cost of additional investments:

$$s_{A_j,B_{j'}} = \frac{\phi_M(N_A^{M^*} + N_B^{M^*})(\theta R - 1) - (N_A^{M^*})^{\psi} - (N_B^{M^*})^{\psi}}{r} - \left\{ N_A^{M^*} + N_B^{M^*} - N_{A,j}^{MP^*} - N_{B,j'}^{MP^*} \right\}.$$

The set of possible agreements is

$$\Pi = \left\{ (\Pi^M_{A_j,B_{j'}}, \Pi^M_{B'_j,A_j}) : \Pi^M_{A_j,B_{j'}} \in [0, s_{A_j,B_{j'}}] \wedge \Pi^M_{B_{j'},A_j} = s_{A_j,B_{j'}} - \Pi^M_{A_j,B_{j'}} \right\}.$$

The Nash bargaining solution solves

$$\max_{(\Pi^M_{A_j,B_{j'}}, \Pi^M_{B'_j,A_j}) \in \Pi} (\Pi^M_{A_j,B_{j'}} - \Pi^{MP}_{A,j})(\Pi^M_{B_{j'},A_j} - \Pi^{MP}_{B,j'})$$

where the expected values in the MP state are the disagreement values. We arrive at the well-known solution that the resulting merger share for a type j bank in market A merging with a type j' bank in market B is

$$\Pi^M_{A_j,B_{j'}} = \frac{1}{2}(s_{A_j,B_{j'}} - \Pi^{MP}_{B,j'} + \Pi^{MP}_{A,j})$$

the remaining merger share goes to the type j' bank in market B. To pinpoint the disagreement values, we discuss the structure of the matching mechanism.

Let M_A denote the measure of banks in market A, and M_B be the measure of banks in market B. Let us define the ratio $\theta_m \equiv M_A/M_B$. This fraction represents the relative scarcity of market-specific assets. If θ_m is high, there are many more banks in market A than in market B, and vice-versa. The number of negotiations per unit of time is given by a matching function $\Upsilon(M_A, M_B)$ that is assumed to be increasing in both arguments, concave and homogeneous of degree one. As each bank experiences the same flow probability of finding a potential partner, the arrival rate of a merger opportunity is a Poisson process. The arrival rate of a merger for a bank in market A is

$$\Upsilon(M_A, M_B)/M_A = \Upsilon\left(1, \frac{M_B}{M_A}\right) \equiv q_A(\theta_m).$$

Technically, we have $q_A'(\theta_m) \leq 0$, the elasticity of $q_A(\theta_m)$ is between zero and one, and satisfies Inada conditions. These properties ensure banks in market A are more likely to match with banks in market B if the ratio of banks in market A to banks in market B is low. Symmetrically, for banks in market B, the arrival rate of mergers is $q_B(\theta_m) \equiv \theta_m q_A(\theta_m)$ with $q_B'(\theta_m) \geq 0$ with a similar interpretation if the ratio is high. A proportionate mass of new banks and entrepreneurs enter both markets to ensure the expected value in each state remains time-invariant for an equilibrium mass of successful mergers M_i. The creation of new banks in market i, m_i, which is also the creation of new entrepreneurs in market i, satisfies $m_i = q_i(\theta_m)M_i$. The types of banks newly created occur with equal likelihood.

For a Δ time, the probability that a bank in market A finds a merger partner is $\Delta q_A(\theta_m)$ with the complement $1-\Delta q_A(\theta)$ that the search must continue. Independent of the search probability, the probability of the MP state ends also occurs. The MP state ending captures that all arbitrage opportunities created from the discovery shock have been captured. The probability that mergers are still viable after a search of time Δ is $e^{-\Delta\lambda^{MP}}$. The expected value in the NM state $\Pi_{i,j}^{NM}$ is obtained by each bank if the MP state ends. The disagreement value of a bank j in market A is

$$\begin{aligned}\Pi_{A,j}^{MP} = &\left[\Delta q_A(\theta_m)\left[\frac{1}{2}\max\{\Pi_{A_j,B_s}^{M}, \Pi_{A,j}^{MP}\} + \frac{1}{2}\max\{\Pi_{A_j,B_l}^{M}, \Pi_{A,j}^{MP}\}\right] e^{-\Delta\lambda^{MP}}\right. \\ &+\{1-\Delta q_A(\theta_m)\}\Pi_{A,j}^{MP} e^{-\Delta\lambda^{MP}} + \Pi_{A,j}^{NM}(1-e^{-\Delta\lambda^{MP}}) \\ &\left.+\Delta\{\phi_{i,j} N_{A,j}^{NM^*}(\theta R - 1) - \left(N_{A,j}^{NM^*}\right)^{\alpha}\}\right] e^{-r\Delta}.\end{aligned}$$

The above expression says the disagreement value (expected value of the NM state) is the discounted expected value of the bank in each future state with interim profits. The likelihood of the bank matching with a potential partner of either type is equally weighted at $1/2$. A merger occurs if and only if the equilibrium merger share is greater than or equal to the continuation value of searching.

6 Equilibrium

As our focus is on assortative matching solutions, we are going to assume a scenario where banks of the same type find it profitable to merge and would rather wait otherwise, that is, $\Pi_{A_j,B_{j'}}^{M} \leq \Pi_{A,j}^{MP}$ for $j \neq j'$. We characterize the solution as a proposition below and arrive at a similar expression as in Rhodes-Kropf and Robinson (2008).

Proposition 6.1 *Assuming mergers are profitable for banks of the same type and not otherwise, that is, $\Pi_{A_j,B_{j'}}^{M} \leq \Pi_{A,j}^{MP}$ and $\Pi_{B_{j'},A_j}^{M} \leq \Pi_{B,j}^{MP}$ for $j \neq j'$ the expected profits in each state for a type j bank in market i is given by*

$$\Pi_{i,j}^{NM} = \left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right)\Pi_{i,j}^{MP} + \frac{r}{\lambda^{NM}+r}X_{i,j},$$

$$\Pi_{i,j}^{MP} = \frac{(4G+q_{i'}(\theta_m))X_{i,j} + q_i(\theta_m)(s_{i_j,i'_j} - X_{i',j})}{4G+q_i(\theta_m)+q_{i'}(\theta_m)},$$

$$\Pi_{i_j,i'_j}^{M} = \frac{(2G+q_{i'}(\theta_m))X_{i,j} + (2G+q_i(\theta_m))(s_{i_j,i'_j} - X_{i',j})}{4G+q_i(\theta_m)+q_{i'}(\theta_m)}.$$

Where $X_{i,j}$ is the discounted sum of profits of a type j bank in market i given by

$$X_{i,j} = \frac{\phi_{i,j} N_{i,j}^{NM^*}(\theta R - 1) - (N_{i,j}^{NM^*})^{\alpha}}{r}$$

and parameter G is

$$G = r\left(\frac{\lambda^{MP} + \lambda^{NM} + r}{\lambda^{NM} + r}\right).$$

Corollary 6.2 provides a sufficient condition to ensure supermodularity of synergies guarantee assortative matching takes place.

Corollary 6.2 *For bank types j, j' where $j \neq j'$ and markets i, i' assortative matching will occur if*

$$4G[s_{i_j,i'_{j'}} - X_{i,j} - X_{i',j'}] + q_{i'}(\theta_m)[s_{i_j,i'_{j'}} - s_{i_{j'},i'_{j'}}] < q_i(\theta_m)[s_{i_j,i'_j} - s_{i_j,i'_{j'}}] \tag{3}$$

holds.

The intuition of the solution set and sufficient condition above says that the expected value of each state is the weighted average of future outcomes, which depends on the bargaining power, gain in a merger, and the likelihood of matching, which are all endogenously determined. The sufficient condition guarantees that when two different types of banks are matched, one party will always reject merging because the higher type bank will capture a greater share of the would-be merger surplus. Thus, banks are incentivized to continue searching until they match with a similar type. Several exogenous variables of interest change the likelihood of assortative matching occurring: the net interest margin of banks, the discount rate of banks, and the monitoring/screening costs for banks.

6.1 Comparative Statics

We examine the likelihood of the assortative matching equilibrium across several dimensions: i) the net interest margin, ii) the discount rate, and iii) cost efficiency. Within our model, the net interest margin (NIM) remains the same before and after a merger,

$$NIM = \theta R - 1.$$

A rise in NIM can be considered an improvement in the riskiness of the loan portfolio (rise in θ) or a rise in the interest charged to borrowers (rise in R). The NIM does not change between a standalone bank or a merged bank. Rather similar in reasoning to Beccalli and Frantz (2013), a change in NIM does impact the likelihood of assortative matching occurring.

The efficiency ratio (E) in our model is defined as the monitoring/screening costs divided by revenues. For a type j bank in market i the efficiency ratio reduces to

$$E = \begin{cases} \frac{\phi_{i,j}(\theta R-1)-r}{\alpha\phi_{i,j}\theta R}, & \text{standalone;} \\ \\ \frac{\phi_M(\theta R-1)-r}{\psi\phi_M\theta R}, & \text{merged.} \end{cases}$$

The efficiency ratio only changes when a merger occurs. Thus, it does not change for a standalone bank, regardless of whether a merger opportunity exists. Rather, the relative efficiency gain (loss) between a standalone and the would-be merged bank affects the likelihood of assortative matching by mechanically changing the potential merger surplus.

We also define the market-to-book ratio (MB ratio) as the ratio of a bank's present value to its equilibrium intangible asset stock. For a type j bank in market i its MB ratio is

$$\text{MB ratio} = \begin{cases} \frac{\Pi_{i,j}^{NM}}{N_{i,j}^{NM*}}, & \text{state } NM; \\ \\ \frac{\Pi_{i,j}^{MP}}{N_{i,j}^{NM*}}, & \text{state } MP. \end{cases}$$

Strictly speaking, our MB ratio only reflects intangible assets. In similar reasoning to Peters and Taylor (2017), our ratio reflects the banks Tobin's q sensitivity of intangible asset investments. An empirical concern is that many US commercial banks are not publicly traded, implying market capitalization values are unavailable. Our MB ratio is intended to act as a conceptual device where bank balance sheets and income statement fundamentals could proxy for counterfactual market capitalization values.

We assume Assumption 5.1 and Corollary 6.2 hold for the following series of propositions below. For analytical convenience, we define simplifying assumptions as when the cost structure is invariant to mergers given by $\alpha = \psi = \gamma$ and identical utilization parameters across markets for a given type, $\phi_{i,j} = \phi_{i',j} = \phi$. It is implicitly implied that the associated ϕ for a type s bank is not necessarily the same value as for a type l bank.[7]

[7]All proofs can be found in the Appendix C.

Proposition 6.3 *When synergy benefits reflect complementarity modeled as $\phi_M = \phi_{i,j} \cdot \phi_{i',j}$. Under simplified assumptions, a higher utilization parameter ϕ corresponds with a higher MB ratio. Thus, assortative matching reflects an ordinal ranking of MB ratios. The bank with the highest MB ratio in market A will merge with the highest one in market B with successive patterns. Analogously, the ex-ante and ex-post efficiency ratios also reflect an ordinal ranking.*

The above stipulates a well-ordering ranking of pre-M&A balance sheet statistics among successful bank M&A deals under complementarity. Banks face a trade-off of realizing the synergy benefits in a merger with the reduction in bargaining power as the difference in types rises. This tension results in an endogenous "like-buys-like" matching equilibrium. Proposition 6.3 suggests that the spread between an acquirer and acquiree MB ratios is expected to be small under complementarity while the spread diverges away from zero under substitutability. These MB spread patterns should correspond to cost efficiency and other balance sheet statistics as well.

Proposition 6.4 *A rise in NIM raises the standalone portion of the MB ratio and has an ambiguous effect on the would-be merger portion. Under simplifying assumptions, a threshold NIM exists where for NIM less than the threshold, a marginal rise lowers the MB ratio in all states, while above the threshold, a marginal rise raises the MB ratio in all states. A rise in synergy benefits raises the NIM threshold. The impact on the likelihood of assortative matching is ambiguous. Under simplifying assumptions, if the synergy benefits are sufficiently high, a rise in NIM increases the likelihood of assortative matching. Lastly, a rise in NIM leads to a decline in the efficiency ratio for both standalone and consolidated banks.*

Proposition 6.4 suggests that the impact on ex-ante balance sheet ratios remains ambiguous. The intuition is that a merged bank requires additional investments proportional to ex-post profitability. This nonlinear trade-off reflects the potential for a merger surplus to decline. When the NIM is sufficiently high, a marginal improvement in profitability translates to an increase in merger surplus. Lastly, our model suggests an improvement in profitability coincides with cost-efficiency gains.

Proposition 6.5 *A rise in the required rate of return declines the standalone portion of the MB ratio and has an ambiguous effect on the would-be merger portion. Under simplifying assumptions and sufficient lower bounds on synergy benefits, the MB ratio declines in all states. The efficiency ratio declines in all states with no change in net interest margin. The impact on the likelihood of assortative matching is ambiguous. Under the same simplifying assumptions, if the synergy benefits are sufficiently high, a rise in the required rate of return lowers the likelihood of assortative matching.*

The above suggests the impact of a rise in the cost of equity on bank balance sheet ratios remains ambiguous. The intuition is that a decline in required merger investments accompanies a decline in the present value of merger profits. Proposition 6.5 suggests that when synergy benefits are sufficiently large, a rise in the cost of equity will always reduce merger surplus and the likelihood of the "like-buys-like" equilibrium. We also find that a rise in the cost of equity also results in cost efficiency gains. Our propositions contribute to reconciling the findings in the literature between ex-ante and ex-post bank merger performance.

6.2 Simulations

In this section, we conduct a set of counterfactual analyses through simulations to investigate the impact of regulations on assortative matching and post-merger efficiency. In our model, ex-ante balance sheet statistics reflect ex-post banking consolidation patterns determined by ex-ante and expected ex-post primitives. In our first simulation, we can express equation (3) in Corollary 6.2 as the following ratio:

$$\text{Ratio} \equiv \frac{4G[s_{A_l,B_s} - X_{A,l} - X_{B,s}] + q_B(\theta_m)[s_{A_l,B_s} - s_{A_s,B_s}]}{q_A(\theta_m)[s_{A_l,B_l} - s_{A_l,B_s}]}, \tag{4}$$

where the Ratio represents the likelihood of assortative matching. The Ratio reflects the balance between gains in synergy from a merger and costs arising from differences in bank characteristics. When the Ratio is below one, it indicates that potential synergies benefits among similar characteristic banks outweigh the associated costs of searching, making assortative matching (mergers of similar banks) more favorable. Conversely, a

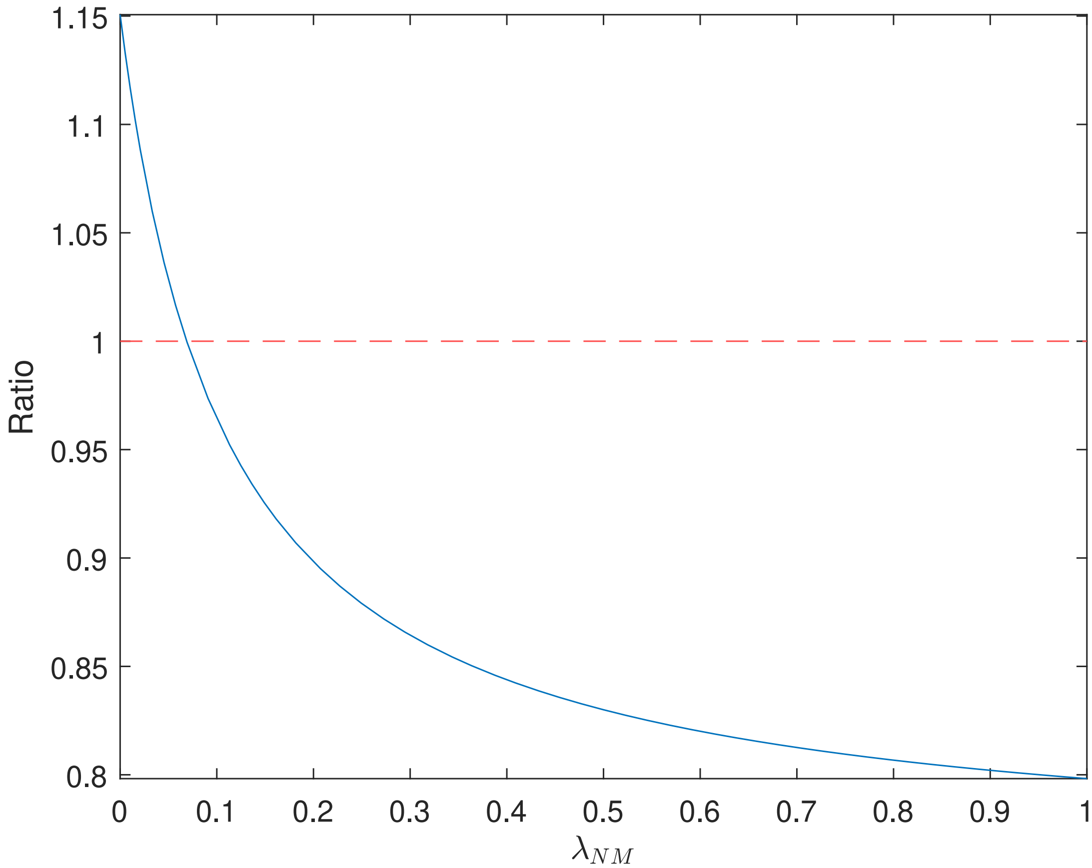
Ratio above one suggests that the marginal costs of searching may outweigh the synergy benefits of banks matching with similar characteristics. Therefore, when the Ratio is less than one, Corollary 6.2 guarantees the assortative matching equilibrium.

To understand why this Ratio matters, we should consider that it captures the regulator's influence on merger patterns by indirectly altering merger incentives. For instance, policies that inhibit banks from entering the merger state raise the search cost of merging, thus decreasing the likelihood of assortative matching. Therefore, the Ratio quantifies a "merger feasibility threshold" that regulators can influence. Suppose a regulator determined the state intensity parameter λ^{NM} in the NM state. This implies the regulator determines with probability $(1 - e^{-\Delta\lambda^{NM}})$ of banks entering the merger state. Hence, by simulating different values for the state intensity parameter λ^{NM}, we investigate the likelihood of achieving assortative matching under varying regulatory conditions.

Table A.5 presents the simulated parameters used in our analysis, where values are either based on observed data moments or set according to reasonable and conventional standards. For example, we use average data moments from the Call Reports database for the net interest margin and the required rate of return (r) approximated by the return on equity (ROE). To set a value for the MP-state intensity, we estimate the likelihood for a given bank-holding company to undergo a merger in the market as the proportion of unique bank-holding company mergers relative to the total number of bank-holding companies in our sample. We set other parameters to ensure the values of intangible assets and equilibrium merger shares remain positive.

Figure 10 illustrates a simulation showing how different λ^{NM} levels influence the Ratio—and thus the likelihood of meeting the assortative matching condition. We can interpret lower λ^{NM} values as being more restrictive. When entry into the merger state is limited by high regulatory barriers, banks with high synergy potential may be unable to merge in the merger state because of an initial mismatch, and re-searching is costlier. This leads to a decline in assortative matching, as banks that would otherwise form efficient mergers may choose suboptimal mergers to exploit an opportune moment.

Figure 10: Likelihood of Assortative Matching



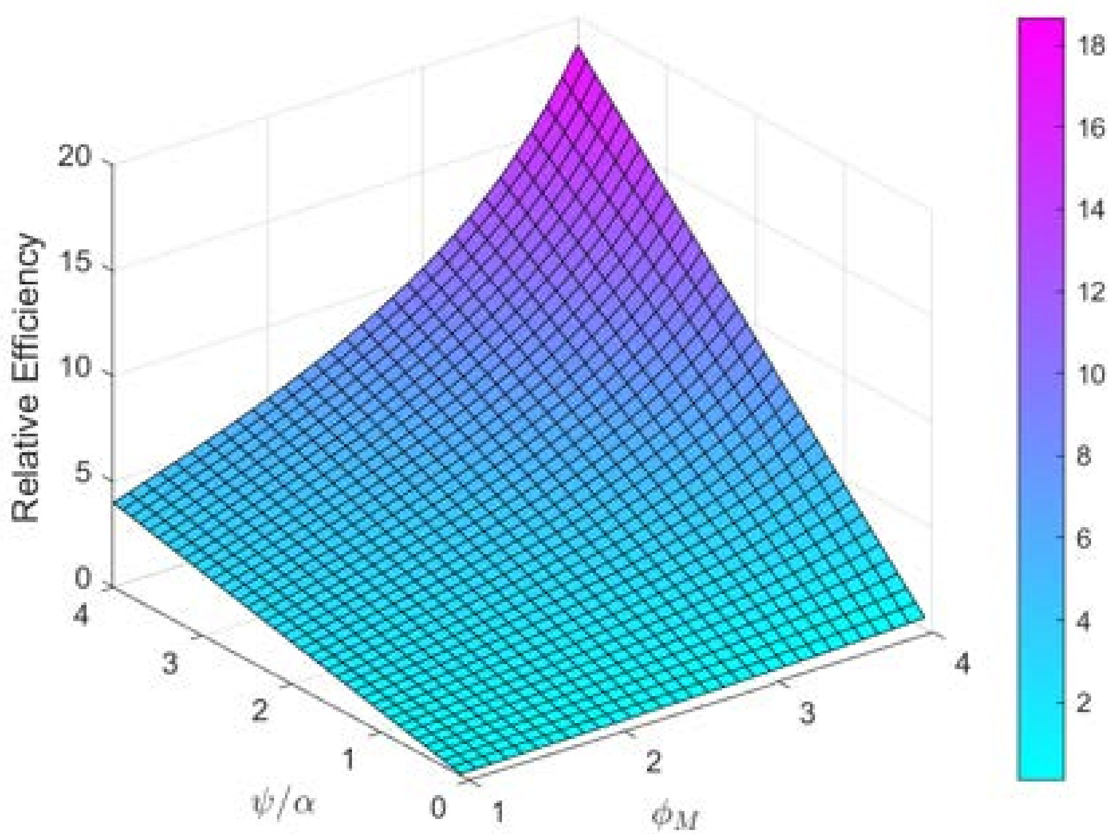
Note: This figure illustrates a simulation by showing how different λ^{NM} (state intensity parameter in the NM state) levels influence the Ratio—and thus the likelihood of meeting the conditions for assortative matching.

Regulators may be concerned with the ex-post efficiency gains (losses) for successful bank M&As under assortative matching. We conceptualize the efficiency ratio as the monitoring and screening costs divided by revenues. The efficiency ratio serves as a measure of a bank's operational efficiency, with lower ratios indicating a higher degree of efficiency. For mergers, this ratio reflects how well-merged entities can balance the costs of monitoring and screening with the revenues they generate. To illustrate this discussion and compare the efficiency ratios between the standalone and merger cases, we define relative efficiency as the ratio of standalone efficiency to merger efficiency as follows:

$$\text{Relative Efficiency} \equiv \frac{\text{Efficiency ratio}_{\text{standalone}}}{\text{Efficiency ratio}_{\text{merged}}}.$$

where a value Relative Efficiency > 1 implies an improvement in efficiency ratios due to the merger. Figure 11 simulates relative efficiency under assortative matching for a same-type bank merger across two dimensions: (i) the ratio of the curvature of the monitoring/screening cost function, ψ/α, and (ii) synergy benefits, ϕ_M.

Figure 11: Relative Efficiency Parameter Space



Note: This figure shows a simulation of changes in relative efficiency (defined as the ratio of standalone efficiency to merger efficiency) with respect to the ratio of the curvature of the monitoring/screening cost function (ψ/α) and synergy benefits (ϕ_M).

An interesting finding is for $\psi/\alpha < 1$, we have Relative Efficiency < 1. This outcome indicates that when the monitoring and screening cost function has a lower curvature post-merger, the efficiency of the merged bank is lower than when they operated independently. However, as synergy benefits (denoted by ϕ_M) increase, these efficiency losses are partially mitigated. Intuitively, in cases where synergy benefits are high, they help reduce the impact of post-merger inefficiencies. Conversely, when $\psi/\alpha > 1$, merged banks achieve efficiency gains because a steeper cost function is associated with higher intangible asset stock, which results in greater marginal revenue. Higher synergy benefits amplify these gains, suggesting that when banks have high synergy potential, mergers are likely to improve overall efficiency in this region with multiples as high as 19.

Our model and simulations show how intangible asset accumulation among banks pre- and post-merger can lead to sizable outcome differences. Figure 10 highlights how regulators can influence the likelihood of assortative matching. Showing that strict regulations can result in the breakdown of the assortative matching equilibrium. While Figure 11 highlights the parameter regions of ex-post bank efficiency. Giving regulators a litmus test of permitting or rejecting bank merger requests under the assortative matching equilibrium with potential efficiency gains beyond ten-fold.

7 Conclusion

The surge in mergers and acquisitions (M&A) within the U.S. commercial banking industry over the past four decades has been a focal point of research. The transition of the U.S. economy towards a knowledge-based model has led to a substantial increase in intangible assets in the financial sector, mirroring trends observed in non-financial sectors. Our paper combines these two important trends in the banking industry and investigates how the accumulation of intangible assets shapes bank M&A strategies and post-merger performance.

Through an empirical framework, we investigate the degree of intangible asset accumulation among banks and its impact on M&A activities. Our analysis reveals three key facts: (i) the intangible asset ratio in the banking industry has increased five-fold over the last thirty years, (ii) there is strong assortative matching between acquirer and target banks in M&A transactions, with acquirer banks tending to merge with target banks that have similar characteristics such as size, loans, net interest income, and intangible assets, and (iii) considering the cyclicality of bank M&A activity and assortative matching, this matching appears to be a general phenomenon rather than a time-specific pattern.

We then investigate the causal impact of intangible asset synergy on post-merger performance through the difference-in-differences methodology, documenting that acquirer banks in the treated group, which experience higher assortative matching in intangible assets at the time of the M&A, exhibit higher and statistically significant loan growth and operating efficiency improvements than the control group. In contrast, we do not find such evidence for acquirer banks with lower assortative matching in intangible assets. Thus, we demonstrate that the overall post-merger performance gains in loan growth and operating efficiency improvements are primarily driven by acquirer banks engaging in higher assortative matching during the M&A process. This highlights the important role of intangible asset synergy in M&A-related bank performance.

To substantiate our empirical evidence, we develop a theoretical search model of bank M&As, illustrating how merging intangible asset stocks drives synergistic benefits in bank consolidations. Utilizing a continuous-time Diamond-Mortensen-Pissarides search model we characterize the assortative matching equilibrium ("like-buys-like") and present several propositions regarding the impact of net interest margin and efficiency ratio on the likelihood of assortative matching.

Our counterfactual analyses through simulations highlight the significant influence of regulatory policies on the dynamics of bank mergers and the resulting efficiency outcomes. The first simulation shows that stricter regulations can diminish the chances of assortative matching by increasing barriers for banks to enter the merger state. The second simulation illustrates how varying synergy benefits interact with cost structures and impact post-merger bank efficiency. Resulting in regions of efficiency gains as high as 19 multiples and other regions of efficiency losses.

Our study contributes to a deeper understanding of the interplay between intangible assets and M&A strategies, which are driving trends in bank consolidations. We argue that these insights provide valuable input for contemporary policy discussions and challenges. One of the critical challenges posed by the growing importance of intangible assets in M&A transactions is their valuation and reporting. Currently, intangible assets such as goodwill, brand value, and intellectual property are often evaluated less rigorously than physical assets despite their significant influence on post-merger performance. Regulatory bodies must ensure that these assets are accurately accounted for when assessing concerns posed by bank M&A applications.

References

Akkus, O., J. A. Cookson, and A. Hortacsu (2016). The determinants of bank mergers: A revealed preference analysis. *Management Science 62*(8), 2241–2258.

Alessandrini, P., G. Calcagnini, and A. Zazzaro (2008). Asset restructuring strategies in bank acquisitions: Does distance between dealing partners matter? *Journal of Banking & Finance 32*(5), 699–713.

Beccalli, E. and P. Frantz (2013). The determinants of mergers and acquisitions in banking. *Journal of Financial Services Research 43*, 265–291.

Bena, J. and K. Li (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance 69*(5), 1923–1960.

Bindal, S., C. H. Bouwman, S. A. Johnson, et al. (2020). Bank regulatory size thresholds, merger and acquisition behavior, and small business lending. *Journal of Corporate Finance 62*, 101519.

Bliss, R. T. and R. J. Rosen (2001). Ceo compensation and bank mergers. *Journal of Financial Economics 61*(1), 107–138.

Carletti, E., P. Hartmann, and G. Spagnolo (2007). Bank mergers, competition, and liquidity. *Journal of Money, Credit and Banking 39*(5), 1067–1105.

Cornett, M. M., J. J. McNutt, and H. Tehranian (2006). Performance changes around bank mergers: Revenue enhancements versus cost reductions. *Journal of Money, Credit and Banking 38*(4), 1013–1050.

Dell'Ariccia, G. and P. Garibaldi (2005). Gross credit flows. *The Review of Economic Studies 72*(3), 665–685.

DeYoung, R., D. D. Evanoff, and P. Molyneux (2009). Mergers and acquisitions of financial institutions: A review of the post-2000 literature. *Journal of Financial Services Research 36*, 87–110.

Drechsler, I., A. Savov, and P. Schnabl (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics 132*(4), 1819–1876.

Drechsler, I., A. Savov, and P. Schnabl (2021). Banking on deposits: Maturity transformation without interest rate risk. *The Journal of Finance 76*(3), 1091–1143.

Focarelli, D., F. Panetta, and C. Salleo (2002). Why do banks merge? *Journal of Money, Credit and Banking 34*(4), 1047–1066.

Granja, J., G. Matvos, and A. Seru (2017). Selling failed banks. *The Journal of Finance 72*(4), 1723–1784.

Levine, R., C. Lin, and Z. Wang (2020). Bank networks and acquisitions. *Management Science 66*(11), 5216–5241.

Li, K., B. Qiu, and R. Shen (2018). Organization capital and mergers and acquisitions. *Journal of Financial and Quantitative Analysis 53*(4), 1871–1909.

Masulis, R. W., S. W. Reza, and R. Guo (2023). The sources of value creation in acquisitions of intangible assets. *Journal of Banking & Finance 154*, 106879.

Peristiani, S. (1997). Do mergers improve the X-efficiency and scale efficiency of us banks? evidence from the 1980s. *Journal of Money, Credit, and Banking 29*(3), 326–337.

Peters, R. H. and L. A. Taylor (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics 123*(2), 251–272.

Ramanna, K. (2008). The implications of unverifiable fair-value accounting: Evidence from the political economy of goodwill accounting. *Journal of Accounting and Economics 45*(2-3), 253–281.

Rhoades, S. A. (1993). Efficiency effects of horizontal (in-market) bank mergers. *Journal of Banking & Finance 17*(2-3), 411–422.

Rhodes-Kropf, M. and D. T. Robinson (2008). The market for mergers and the boundaries of the firm. *The Journal of Finance 63*(3), 1169–1211.

Seru, A. (2014). Firm boundaries matter: Evidence from conglomerates and r&d activity. *Journal of financial economics 111*(2), 381–405.

Shalev, R., I. X. Zhang, and Y. Zhang (2013). Ceo compensation and fair value accounting: Evidence from purchase price allocation. *Journal of Accounting Research 51*(4), 819–854.

Shimer, R. and L. Smith (2000). Assortative matching and search. *Econometrica 68*(2), 343–369.

Topkis, D. M. (1998). *Supermodularity and complementarity*. Princeton University Press.

Appendix A Tables

Table A.1: Bank Balance Sheet Variables and Descriptions - U.S. Call Reports

Variables	Description
Net Loans	Loans and Leases Net of Unearned Income and Loss Allowance (*loansnet*)
Intangible Assets	Other Intangible Assets (*RCFD3163/RCON3163 or RCFD0426/RCON0426*)
Tangible Assets	Premises and fixed assets (including capitalized leases) (*RCFD2145/RCON2145*) + Other real estate owned (*RCFD2150/RCON2150*)
Intangible Asset Ratio	$\frac{\text{Intangible Assets}}{\text{Total Assets}}$
Operating Efficiency	$\frac{\text{Operating Income}}{\text{Non-interest Expenses}}$

Note: This table presents the bank balance sheet variables and descriptions in the U.S. Call Reports sample.

Table A.2: Summary Statistics - Quarterly U.S. Call Reports

	Mean	SD	Median	Min	Max	Count
Assets	706935.51	18938206.85	52703.00	0.00	2.69×10^9	1736167.00
Deposits	438863.69	10823290.17	45681.00	0.00	1.58×10^9	1736166.00
Loans and Leases Net of Unearned Income and Loss Allowance	392215.30	8976383.75	27888.00	-150.00	1.03×10^9	1736167.00
Net Interest Income	7168.86	146009.40	695.00	-1.20×10^7	18662000.00	1271806.00
Equity	69318.92	1904919.91	4884.00	-939749.00	2.57×10^8	1736166.00
Operating Efficiency	2.69	9.97	2.49	-1197.00	10397.45	1271624.00

Note: This table presents the summary statistics for selected bank-level quarterly variables from the U.S. Call Reports.

Table A.3: Summary Statistics - Number of M&A per Year at the Bank Holding Company Level

	Mean	SD	Median	Min	Max	Count
Number of M&A	1.41	1.27	1.00	1.00	20.00	5524.00

Note: This table documents the summary statistics of number of M&A per year at the bank holding company level.

Table A.4: Summary Statistics - Quarterly Bank-level Intangible Asset Components

	Mean	SD	Median	Min	Max	Count
Total Intangible Assets	20580.65	649792.51	0.00	0.00	79167392.00	1345942.00
Goodwill	17340.70	541894.40	0.00	0.00	57347716.00	1216422.00
Other Intangible Assets	5418.72	194780.67	0.00	0.00	28750000.00	1216422.00
Tangible Assets	8793.86	151742.79	963.00	0.00	23435000.00	1749255.00

Note: This table documents the summary statistics of the intangible asset components and tangible assets in the quarterly U.S. Call Reports.

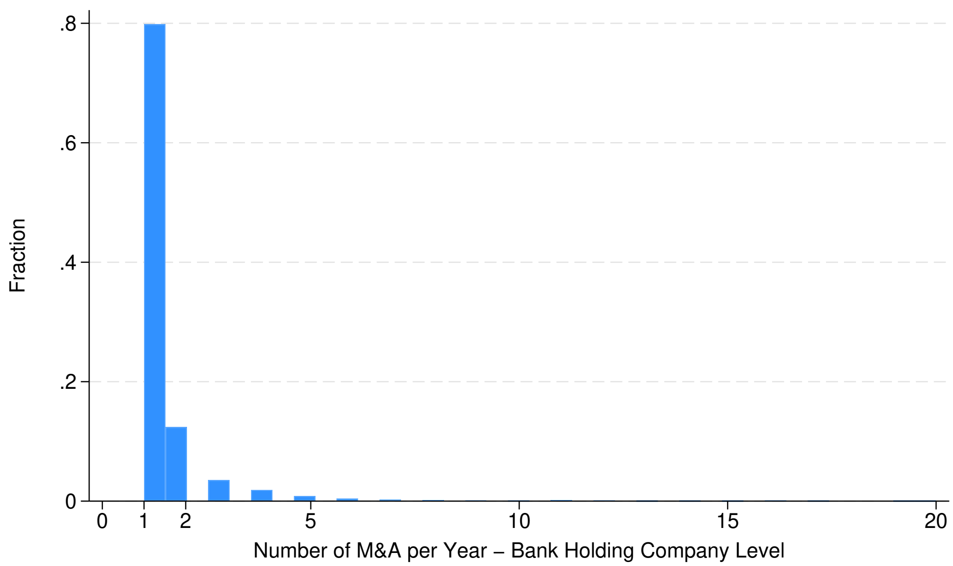
Table A.5: Simulation Parameters

Variable	Parameter	Value	Source
Net interest margin	$\theta R - 1$	0.02	Average net interest margin in the U.S. Call Reports sample
Discount rate	r	0.11	Average return on equity in the U.S. Call Reports sample
MP-state intensity	λ^{MP}	0.10	$\frac{\text{Number of unique bank-holding company mergers (in the M\&A sample)}}{\text{Total number of bank-holding company (in the U.S. Call Reports sample)}}$
Arrival rate of a merger	$q_A(\theta_m), q_B(\theta_m)$	0.50	Exogenous equilibrium parameter
Cost Structure	ψ, α	1.05	Value which makes equilibrium intangible assets and merger share positive
Type-s bank parameter	$\phi_{A,s}, \phi_{B,s}$	8.0	Value which makes equilibrium intangible assets and merger share positive
Type-l bank parameter	$\phi_{A,l}, \phi_{B,l}$	8.4	Value which makes equilibrium intangible assets and merger share positive

Note: This table shows the simulated parameters. In both simulations, we model complementarity of synergy benefits as $\phi_j^M = \phi_{A,j} * \phi_{B,j}$ for $j = l, s$. That is, the bank parameter remains identical across markets for the same type. We only require the net interest margin and discount rate values for the relative efficiency simulation.

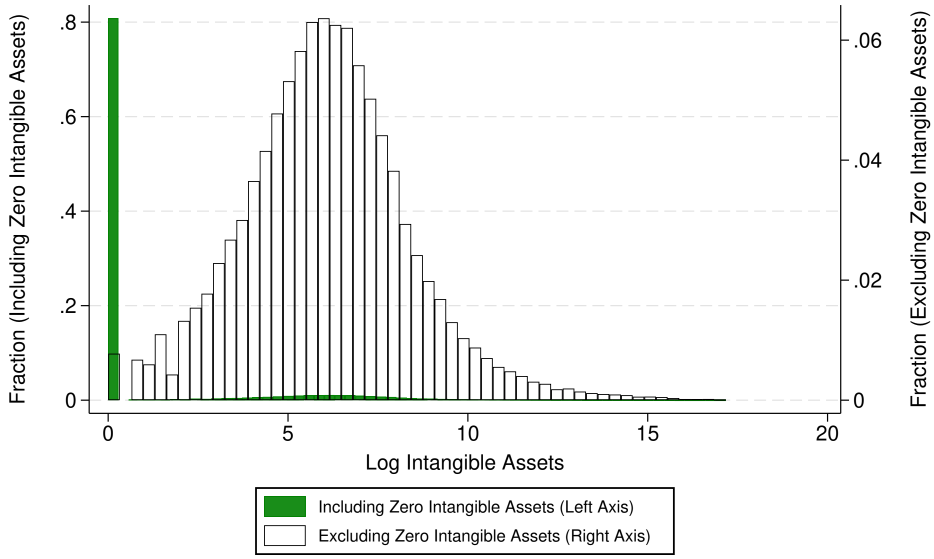
Appendix B Figures

Figure B.1: Histogram - Number of M&A per Year at the Bank Holding Company Level



Note: This figure documents the histogram of the number of M&A per year at the bank holding company level.

Figure B.2: Histogram - Log Intangible Assets



Note: This figure presents the histogram of the logarithm of intangible assets (excluding goodwill) from the quarterly U.S. Call Reports. The left axis displays the histogram of the logarithm of intangible assets (excluding goodwill), including zero values, while the right axis shows the histogram of the logarithm of non-zero intangible assets (excluding goodwill).

Appendix C Derivations

C.1 Proof of Proposition 6.1

The proof is very similar to Rhodes-Kropf and Robinson (2008). Without loss of generality, we shall derive the expected profits for a type $j \in s, l$ bank in market A. Under the assumption we have

$$\Pi_{A,j}^{MP} = \Gamma_{A1}(\Delta)\Pi_{A_j,B_j}^{M} + \Gamma_{A2}(\Delta)\Pi_{A,j}^{NM} + \Gamma_{A3}(\Delta),$$

where

$$\Gamma_{A1}(\Delta) = \frac{1/2\Delta q_A(\theta_m)\exp(-\Delta\lambda^{MP})\exp(-r\Delta)}{1-(1-(1/2)\Delta q_i(\theta_m))\exp(-\Delta\lambda^{MP})\exp(-r\Delta)},$$

$$\Gamma_{A2}(\Delta) = \frac{(1-\exp(-\Delta\lambda^{MP}))\exp(-r\Delta)}{1-(1-(1/2)\Delta q_i(\theta_m))\exp(-\Delta\lambda^{MP})\exp(-r\Delta)},$$

$$\Gamma_{A3}(\Delta) = \frac{\Delta\left\{\phi_{A,j}N_{A,j}^{NM*}(\theta R-1)-(N_{A,j}^{NM*})^{\alpha}\right\}\exp(-r\Delta)}{1-(1-(1/2)\Delta q_i(\theta_m))\exp(-\Delta\lambda^{MP})\exp(-r\Delta)}.$$

The solution to $\Pi^M_{A_j,B_j}$ is the Nash bargaining solution. We arrive at

$$(1-\frac{1}{2}\Gamma_{A1}(\Delta))\Pi^{NM}_{A,j}=\frac{1}{2}\Gamma_{A1}(\Delta)s_{A_j,B_j}-\frac{1}{2}\Gamma_{A1}(\Delta)\Pi^{MP}_{B,j}+\Gamma_{A2}(\Delta)\Pi^{NM}_{A,j}+\Gamma_{A3}(\Delta).$$

We also arrive at the second equation

$$\Pi^{NM}_{A,j}=\Gamma_{A4}(\Delta)\Pi^{MP}_{A,j}+\Gamma_{A5}(\Delta)$$

where

$$\Gamma_{A4}(\Delta)=\frac{(1-\exp(-\Delta\lambda^{NM}))\exp(-r\Delta)}{1-\exp(-\Delta\lambda^{NM})\exp(-r\Delta)},$$

$$\Gamma_{A5}(\Delta)=\frac{\Delta\left\{\phi_{A,j}N^{NM^*}_{A,j}(\theta R-1)-(N^{NM^*}_{A,j})^{\alpha}\right\}\exp(-r\Delta)}{1-\exp(-\Delta\lambda^{NM})\exp(-r\Delta)}.$$

Substituting $\Pi^{NM}_{A,j}$ we arrive at

$$\Pi^{MP}_{A,j}=\frac{(1/2)\Gamma_{A1}(\Delta)s_{A_j,B_j}-(1/2)\Gamma_{A1}(\Delta)\Pi^{MP}_{B,j}+\Gamma_{A2}(\Delta)\Gamma_{A5}(\Delta)+\Gamma_{A3}(\Delta)}{1-\Gamma_{A2}(\Delta)\Gamma_{A4}(\Delta)-(1/2)\Gamma_{A1}(\Delta)}.$$

As the model is continuous time, let us take the limit as $\Delta\to 0$. We have

$$\lim_{\Delta\to 0}\Gamma_{A1}(\Delta)=\frac{(1/2)q_A(\theta_m)}{\lambda^{MP}+r+(1/2)q_A(\theta_m)},$$

$$\lim_{\Delta\to 0}\Gamma_{A2}(\Delta)=\frac{\lambda^{MP}}{\lambda^{MP}+r+(1/2)q_A(\theta_m)},$$

$$\lim_{\Delta\to 0}\Gamma_{A3}(\Delta)=\frac{\phi_{A,j}N^{NM^*}_{A,j}(\theta R-1)-(N^{NM^*}_{A,j})^{\alpha}}{\lambda^{MP}+r+(1/2)q_A(\theta_m)},$$

$$\lim_{\Delta\to 0}\Gamma_{A4}(\Delta)=\frac{\lambda^{NM}}{\lambda^{NM}+r},$$

$$\lim_{\Delta\to 0}\Gamma_{A5}(\Delta)=\frac{\phi_{A,j}N^{NM^*}_{A,j}(\theta R-1)-(N^{NM^*}_{A,j})^{\alpha}}{\lambda^{NM}+r}.$$

We arrive at

$$\Pi_{A,j}^{MP} = \frac{\frac{1}{4}q_A(\theta_m)s_{A_j,B_j} - \frac{1}{4}q_A(\theta_m)\Pi_{B,j}^{MP} + \left(\frac{\lambda^{MP}}{\lambda^{NM}+r}+1\right)\{\phi_{A,j}N_{A,j}^{NM^*}(\theta R-1) - (N_{A,j}^{NM^*})^\alpha\}}{\frac{1}{\lambda^{MP}+r-(1/2)q_A(\theta_m)} - \lambda^{MP}\left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right) - \frac{1}{4}q_A(\theta_m)}$$

and symmetrically

$$\Pi_{B,j}^{MP} = \frac{\frac{1}{4}q_B(\theta_m)s_{A_j,B_j} - \frac{1}{4}q_B(\theta_m)\Pi_{A,j}^{MP} + \left(\frac{\lambda^{MP}}{\lambda^{NM}+r}+1\right)\{\phi_{B,j}N_{B,j}^{NM^*}(\theta R-1) - (N_{B,j}^{NM^*})^\alpha\}}{\frac{1}{\lambda^{MP}+r-(1/2)q_B(\theta_m)} - \lambda^{MP}\left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right) - \frac{1}{4}q_B(\theta_m)}.$$

Making the appropriate substitutions and defining $G = \lambda^{MP} - \lambda^{MP}\left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right) + r$ and the market capitalization of each bank before merger which is defined as the discounted sum of profits,

$$X_{i,j} = \frac{\phi_{i,j}N_{i,j}^{NM^*}(\theta R-1) - (N_{A,j}^{NM^*})^\alpha}{r}.$$

We arrive at

$$\Pi_{A,j}^{MP} = \frac{(4G + q_B(\theta_m))X_{A,j} + q_A(\theta_m)(s_{A_j,B_j} - X_{B,j})}{4G + q_A(\theta_m) + q_B(\theta_m)}.$$

The Nash bargaining solution implies the expected profits from a merger are

$$\Pi_{A_j,B_j}^{M} = \frac{(2G + q_B(\theta_m))X_{A,j} + (2G + q_A(\theta_m))(s_{A_j,B_j} - X_{B,j})}{4G + q_A(\theta_m) + q_B(\theta_m)}$$

with the expected value in the NM state being

$$\Pi_{A,j}^{NM} = \left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right)\Pi_{A,j}^{MP} + \frac{\phi_{A,j}N_{A,j}^{NM^*}(\theta R-1) - (N_{A,j}^{NM^*})^\alpha}{\lambda^{NM}+r}.$$

Lastly, to ensure the solution is a stable equilibria, we require $\Pi_{A_j}^{MP} < \Pi_{A_j,B_j}^{M}$. We arrive at the inequality

$$0 < s_{A_j,B_j} - X_{A,j} - X_{B,j}$$

which holds as long as there are synergy benefits to merge. □

C.2 Proof of Corollary 6.2

We require $\Pi^{M}_{i_j,i'_{j'}} < \Pi^{MP}_{i,j}$ which simplifies to $s_{i_j,i'_{j'}} - \Pi^{MP}_{i',j'} < \Pi^{MP}_{i,j}$. We can make the appropriate substitutions from Proposition 6.1, and the inequality follows. Similarly, when banks of the same type are matched, we also require $\Pi^{M}_{i_j,i'_j} > \Pi^{MP}_{i,j}$ which simplifies to $s_{i_j,i'_j} - \Pi^{MP}_{i',j} > \Pi^{MP}_{i,j}$ which holds as synergy benefits are positive. □

C.3 Proof of Proposition 6.3

We wish to examine how a marginal rise in the utilization parameter $\phi_{i,j}$ impacts a type j banks' MB ratios in market i under complementarity synergy benefits, i.e., $\phi_M = \phi_{i,j}\phi_{i',j}$. Let us examine under simplified assumptions: $\alpha = \psi = \gamma$ and without loss of generality, let us assume that $\phi_{i,j}$ has the higher utilization, that is, $\phi_{i,j} > \phi_{i',j}$. We can decompose the MB ratios in terms of a bank's standalone value and merger potential in each state as

$$\frac{\Pi^{MP}_{i,j}}{N^{NM*}_{i,j}} = \frac{X_{i,j}}{N^{NM*}_{i,j}} + \frac{\Pi^{MP}_{i,j} - X_{i,j}}{N^{NM*}_{i,j}},$$

$$\frac{\Pi^{NM}_{i,j}}{N^{NM*}_{i,j}} = \left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right)\frac{\Pi^{MP}_{i,j}}{N^{NM*}_{i,j}} + \left(\frac{r}{\lambda^{NM}+r}\right)\frac{X_{i,j}}{N^{NM*}_{i,j}}.$$

Let us define the following functions

$$\begin{aligned}
\Gamma &\equiv \frac{X_{i,j}}{N^{NM*}_{i,j}} = \frac{(\alpha-1)\phi_{i,j}(\theta R-1)+r}{\alpha r},\\
\Phi &\equiv \frac{s_{i_j,i'_j} - X_{i,j} - X_{i',j}}{N^{NM*}_{i,j}}\\
&= 2\left[\frac{\alpha^{\frac{1}{\alpha-1}}[\phi_M(\theta R-1)-r]^{\frac{1}{\psi-1}}}{\psi^{\frac{1}{\psi-1}}[\phi_{i,j}(\theta R-1)-r]^{\frac{1}{\alpha-1}}}\right]\left[\frac{(\psi-1)\phi_M(\theta R-1)+(1-\psi)r}{\psi r}\right]\\
&- \left[\frac{\phi_{i',j}(\theta R-1)-r}{\phi_{i,j}(\theta R-1)-r}\right]^{\frac{1}{\alpha-1}}\left[\frac{(1+\alpha)\phi_{i',j}(\theta R-1)-(1+\alpha)r}{\alpha r}\right]\\
&- \left[\frac{(1+\alpha)\phi_{i,j}(\theta R-1)-(1+\alpha)r}{\alpha r}\right]\\
\Lambda &\equiv \frac{q_i(\theta_m)}{4G+q_i(\theta_m)+q_{i'}(\theta_m)}.
\end{aligned}$$

We can re-express the MB ratios as

$$\frac{\Pi_{i,j}^{MP}}{N_{i,j}^{NM*}} = \Gamma + \Lambda\Phi,$$
$$\frac{\Pi_{i,j}^{NM}}{N_{i,j}^{NM*}} = \Gamma + \left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right)\Lambda\Phi.$$

The Γ function represents the standalone portion of an MB ratio, while Φ represents the MB ratio attributed to merger potential, and Λ represents the cost of searching for a potential merger. We have partial derivatives

$$\frac{\partial}{\partial\phi_{i,j}}\frac{\Pi_{i,j}^{MP}}{N_{i,j}^{NM*}} = \frac{\partial\Gamma}{\partial\phi_{i,j}} + \Lambda\frac{\partial\Phi}{\partial\phi_{i,j}}$$
$$\frac{\partial}{\partial\phi_{i,j}}\frac{\Pi_{i,j}^{NM}}{N_{i,j}^{NM*}} = \frac{\partial\Gamma}{\partial\phi_{i,j}} + \left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right)\Lambda\frac{\partial\Phi}{\partial\phi_{i,j}}.$$

We arrive at

$$\frac{\partial\Gamma}{\partial\phi_{i,j}} = \frac{(\gamma-1)(\theta R-1)}{\gamma r} > 0,$$
$$\frac{\partial\Phi}{\partial\phi_{i,j}} = \frac{2(\theta R-1)\left[\frac{\phi_{i,j}\phi_{i',j}(\theta R-1)-r}{\phi_{i,j}(\theta R-1)-r} + (\gamma-1)\phi_{i',j}+1\right]\left[\frac{\phi_{i,j}\phi_{i',j}(\theta R-1)-r}{\phi_{i,j}(\theta R-1)-r}\right]^{\frac{1}{\gamma-1}} - (1+\gamma)(\theta R-1)}{\gamma r}$$
$$+ \frac{(1+\gamma)(\theta R-1)\left[\frac{\phi_{i',j}(\theta R-1)-r}{\phi_{i,j}(\theta R-1)-r}\right]^{\frac{1}{\gamma-1}}}{(1-\gamma)\gamma r} > 0.$$

Under complementarity synergy benefits, a rise in a bank's quality corresponds with a rise in MB ratios in all states. The assortative matching equilibrium implies that the highest-quality bank in market A (with the largest MB ratio in A) matches the highest-quality bank in market B (with the largest MB ratio in B). That is, assortative matching corresponds with an ordinal ranking of MB ratios. Since $\frac{\partial E}{\partial\phi_{i,j}} > 0$, an ordinal ranking of efficiency ratios also holds. $\square$

C.4 Proof of Proposition 6.4

A rise in the net interest margin may come from a reduction in the riskiness of the loan portfolio or a rise in the gross return of loans. Within our framework, we deem both variables to be exogenous. Rather than examining the impact of a change for each variable, we consider a change in the net interest margin (NIM) balance sheet statistic. Using the same definitions in the previous proof, we have

$$\begin{aligned}
\frac{\partial}{\partial NIM}\frac{\Pi_{i,j}^{MP}}{N_{i,j}^{NM*}} &= \frac{\partial\Gamma}{\partial NIM} + \Lambda\frac{\partial\Phi}{\partial NIM}, \\
\frac{\partial}{\partial NIM}\frac{\Pi_{i,j}^{NM}}{N_{i,j}^{NM*}} &= \frac{\partial\Gamma}{\partial NIM} + \left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right)\Lambda\frac{\partial\Phi}{\partial NIM}.
\end{aligned}$$

It suffices to show the signs of $\frac{\partial\Gamma}{\partial NIM}$ and $\frac{\partial\Phi}{\partial NIM}$. We have

$$\begin{aligned}
\frac{\partial\Gamma}{\partial NIM} &= \frac{(\alpha-1)\phi_{i,j}}{\alpha r} > 0, \\
\frac{\partial\Phi}{\partial NIM} &= -\frac{\left\{(\alpha^2-1)(\phi_{i,j}+\phi_{i',j}) - \frac{r(1+\alpha)(\phi_{i',j}-\phi_{i,j})}{\phi_{i,j}(\theta R-1)-r}\right\}\left[\frac{\phi_{i',j}(\theta R-1)-r}{\phi_{i,j}(\theta R-1)-r}\right]^{\frac{1}{\alpha-1}}}{\alpha(\alpha-1)r} \\
&\quad - \frac{2\alpha^{\frac{1}{\alpha-1}}(\psi-1)\phi_{i,j}}{\psi^{\frac{\psi}{\psi-1}}(\alpha-1)r}\frac{[\phi_M(\theta R-1)-r]^{\frac{\psi}{\psi-1}}}{[\phi_{i,j}(\theta R-1)-r]^{\frac{\alpha}{\alpha-1}}} \\
&\quad + \frac{2\alpha^{\frac{1}{\alpha-1}}(\psi+\phi_M-1)}{\psi^{\frac{\psi}{\psi-1}}}\frac{[\phi_M(\theta R-1)-r]^{\frac{1}{\psi-1}}}{[\phi_{i,j}(\theta R-1)-r]^{\frac{1}{\alpha-1}}}.
\end{aligned}$$

The sign of the merger portion of the MB ratio remains ambiguous. As NIM rises, the decision to merge faces a trade-off. On the one hand, synergy benefits are amplified, while on the other, higher required investments reduce merger surplus. Under the same simplified assumptions of $\alpha = \psi = \gamma$ and $\phi_{i,j} = \phi_{i',j} = \phi$ the standalone and merger portions can be expressed as

$$\begin{aligned}
\frac{\partial\Gamma}{\partial NIM} &= \frac{(\gamma-1)\phi}{\gamma r}, \\
\frac{\partial\Phi}{\partial NIM} &= -\frac{2(\gamma+1)\phi}{\gamma r} - \frac{2\phi}{\gamma r}\left[\frac{\phi_M(\theta R-1)-r}{\phi(\theta R-1)-r}\right]^{\frac{\gamma}{\gamma-1}} + \frac{2(\gamma+\phi_M-1)}{\gamma}\left[\frac{\phi_M(\theta R-1)-r}{\phi(\theta R-1)-r}\right]^{\frac{1}{\gamma-1}} \\
&= \frac{2}{\gamma r}\left\{r(\gamma+\phi_M-1)\left[\frac{\phi_M(\theta R-1)-r}{\phi(\theta R-1)-r}\right]^{\frac{1}{\gamma-1}} - \phi\left[\frac{\phi_M(\theta R-1)-r}{\phi(\theta R-1)-r}\right]^{\frac{\gamma}{\gamma-1}} - \phi(\gamma+1)\right\}.
\end{aligned}$$

We shall establish conditions when $\frac{\partial}{\partial NIM}\frac{\Pi_{i,j}^{MP}}{N_{i,j}^{NM*}} \geq 0$. We end up with the following inequality:

$$\underbrace{\left\{\frac{1}{\Lambda}\frac{(\gamma-1)}{2}-(1+\gamma)\right\}}_{LHS} \geq \underbrace{\left[\frac{\phi_M(\theta R-1)-r}{\phi(\theta R-1)-r}\right]^{\frac{\gamma}{\gamma-1}} - r[\phi_M+\gamma-1]\left[\frac{\phi_M(\theta R-1)-r}{\phi(\theta R-1)-r}\right]^{\frac{1}{\gamma-1}}}_{RHS}.$$

Similarly for $\frac{\partial}{\partial NIM}\frac{\Pi_{i,j}^{NM}}{N_{i,j}^{NM*}} \geq 0$ we have the inequality

$$\left\{\left(\frac{\lambda^{NM}+r}{\lambda^{NM}}\right)\frac{1}{\Lambda}\frac{(\gamma-1)}{2}-(1+\gamma)\right\} \geq \text{RHS}.$$

We observe that the sign of the MB ratio in the MP state determines the sign of the MB ratio in the NM state. We note that $NIM > 0$ must hold. Otherwise, it would be optimal for the bank to shut down. We have $NIM \in (0, \infty)$ to consider. We document

$$\lim_{NIM\to\infty} RHS = \left(\frac{\phi_M}{\phi}\right)^{\frac{\gamma}{\gamma-1}} - r[\phi_M+\gamma-1]\left(\frac{\phi_M}{\phi}\right)^{\frac{1}{\gamma-1}}.$$

As the RHS is a decreasing function of NI, if the LHS is greater than the limit, then there exists an NIM^* such that for $NIM \in (0, NIM^*]$ the MB ratio declines and for $NIM \in (NIM^*, \infty)$ the MB ratio increases. The intuition is that if the NIM is low, a marginal gain in NIM leads to a loss in merger surplus due to a disproportionate increase in required investments. If the NIM is sufficiently high, then a marginal gain in NIM amplifies synergy benefits in loan issuance beyond the required investments. We also observe that as synergy ϕ_M rises, the threshold NIM^* increases. We have the counterintuitive result that the MB ratio may decline as synergy benefits rise.

To examine the likelihood of the assortative matching equilibrium holding, we use the function Ξ previously defined. We focus our attention on

$$\frac{\partial \Xi}{\partial NIM} = \Lambda_i\frac{\partial \Phi_j}{\partial NIM} + \Lambda_{i'}\frac{\partial \Phi_{j'}}{\partial NIM} - \frac{\partial \Phi_{j,j'}}{\partial NIM}.$$

Under our simplifying assumptions, we have

$$\frac{\partial \Phi_j}{\partial NIM} = \frac{2\phi_M^j}{r}\left[\frac{\phi_M^j(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}} - \frac{2(1+\gamma)}{r(\gamma-1)}\left[\frac{\phi_j(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}},$$

$$\frac{\partial \Phi_{j'}}{\partial NIM} = \frac{2\phi_M^{j'}}{r}\left[\frac{\phi_M^{j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}} - \frac{2(1+\gamma)}{r(\gamma-1)}\left[\frac{\phi_{j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}},$$

$$\begin{aligned}\frac{\partial \Phi_{j,j'}}{\partial NIM} = &\frac{2\phi_M^{j,j'}}{r}\left[\frac{\phi_M^{j,j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}} - \frac{1+\gamma}{r(\gamma-1)}\left[\frac{\phi_{j}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}\\ &- \frac{1+\gamma}{r(\gamma-1)}\left[\frac{\phi_{j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}.\end{aligned}$$

Then we have

$$\begin{aligned}\frac{\partial \Xi}{\partial NIM} =&\frac{q_i(\theta_m)}{2G+1/2q_i(\theta_m)+1/2q_{i'}(\theta_m)}\frac{\phi_M^{j}}{r}\left[\frac{\phi_M^{j}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}\\ &+\frac{\theta_m q_i(\theta_m)}{2G+1/2q_i(\theta_m)+1/2q_{i'}(\theta_m)}\frac{\phi_M^{j'}}{r}\left[\frac{\phi_M^{j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}\\ &-\frac{2\phi_M^{j,j'}}{r}\left[\frac{\phi_M^{j,j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}\\ &+\frac{2G-1/2q_i(\theta_m)+1/2q_{i'}(\theta_m)}{2G+1/2q_i(\theta_m)+1/2q_{i'}(\theta_m)}\frac{1+\gamma}{r(\gamma-1)}\left[\frac{\phi_{j}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}\\ &+\frac{2G-1/2q_{i'}(\theta_m)+1/2q_{i}(\theta_m)}{2G+1/2q_i(\theta_m)+1/2q_{i'}(\theta_m)}\frac{1+\gamma}{r(\gamma-1)}\left[\frac{\phi_{j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}.\end{aligned}$$

We observe if synergy benefits ϕ_M^j and $\phi_M^{j'}$ are both sufficiently high then $\frac{\partial \Xi}{\partial NIM} > 0$. Lastly, we have

$$\frac{\partial E}{\partial NIM} = \begin{cases} \frac{r-\phi_{i,j}}{\alpha\phi_{i,j}[\theta R-2]^2}, & \text{standalone;}\\ \frac{r-\phi_{i,j}}{\alpha\phi_{M}[\theta R-2]^2}, & \text{merged.}\end{cases}$$

Since $\phi_M > \phi_{i,j} > r$, the efficiency ratio declines. □

C.5 Proof of Proposition 6.5

We have

$$\begin{aligned}\frac{\partial}{\partial r}\frac{\Pi_{i,j}^{MP}}{N_{i,j}^{NM*}} &= \frac{\partial\Gamma}{\partial r} + \frac{\partial\Lambda}{\partial r}\Phi + \Lambda\frac{\partial\Phi}{\partial r},\\ \frac{\partial}{\partial r}\frac{\Pi_{i,j}^{NM}}{N_{i,j}^{NM*}} &= \frac{\partial\Gamma}{\partial r} - \frac{\lambda^{NM}}{(\lambda^{NM}+r)^2}\Lambda\Phi + \left(\frac{\lambda^{NM}}{\lambda^{NM}+r}\right)\left\{\frac{\partial\Lambda}{\partial r}\Phi + \Lambda\frac{\partial\Phi}{\partial r}\right\}.\end{aligned}$$

As Γ, Λ, Φ are positive, we will decompose and examine the partial derivatives of each function separately. We have

$$\frac{\partial \Gamma}{\partial r} = -\frac{(\alpha-1)\phi_{i,j}(\theta R-1)}{\alpha r^2} < 0.$$

A rise in the r will always lead to a decline in the standalone portion of the MB ratio. Similarly,

$$\frac{\partial \Lambda}{\partial r} = -\frac{4q_i(\theta_m)}{(4G+q_i(\theta_m)+q_{i'}(\theta_m))^2}\left\{\frac{\lambda^{MP}\lambda^{NM}}{(\lambda^{NM}+r)^2}+1\right\} < 0.$$

A rise in the r will always increase search costs.

$$\begin{aligned}
\frac{\partial \Phi}{\partial r} &= \frac{\alpha+1}{\alpha r^2}\left\{\phi_{i,j}(\theta R-1)+\phi_{i',j}(\theta R-1)\left(\frac{\phi_{i',j}(\theta R-1)-r}{\phi_{i,j}(\theta R-1)-r}\right)^{\frac{1}{\alpha-1}}\right\} \\
&+\frac{(1+\alpha)[\phi_{i',j}(\theta R-1)-r]}{\alpha(\alpha-1)r}\left(\frac{\phi_{i',j}(\theta R-1)}{\phi_{i,j}(\theta R-1)}\right)^{\frac{2-\alpha}{\alpha-1}}\left(\frac{(\phi_{i,j}-\phi_{i',j})(\theta R-1)}{[\phi_{i,j}(\theta R-1)-r]^2}\right) \\
&-\frac{2\alpha^{\frac{1}{\alpha-1}}[\phi_M(\theta R-1)-r]^{\frac{1}{\psi-1}}}{\psi^{\frac{\psi}{\psi-1}}r^2[\phi_{i,j}(\theta R-1)-r]^{\frac{1}{\alpha-1}}}\{(\psi-1)[\phi_M(\theta R-1)]+r\} \\
&+\frac{2(\psi-1)\alpha^{\frac{1}{\alpha-1}}}{(1+\alpha)\psi^{\frac{\psi}{\psi-1}}r}\frac{[\phi_M(\theta R-1)-r]^{\frac{\psi}{\psi-1}}}{[\phi_{i,j}(\theta R-1)-r]^{\frac{1}{\alpha-1}}}.
\end{aligned}$$

We observe the sign of $\frac{\partial \Phi}{\partial r}$ remains ambiguous. As the required return increases, gains from synergy benefits are reduced while required investments are also lowered, leading to an ambiguous effect on merger surplus. More generally, the cost structures α, ψ and the relative bargaining power between both parties given by the difference $\phi_{i,j}-\phi_{i',j}$ impact the magnitude of sign changes. To arrive at a more tractable solution, consider the following simplifying assumptions: same cost structure $\alpha=\psi=\gamma$ and same utilization between both parties $\phi_{i,j}=\phi_{i',j}=\phi$. We arrive at

$$\begin{aligned}
\frac{\partial \Phi}{\partial r} &= \frac{2(1+\gamma)}{\gamma r^2}[\phi(\theta R-1)] \\
&-\frac{2}{(1+\gamma)\gamma r^2}\left[\frac{\phi_M(\theta R-1)-r}{\phi(\theta R-1)-r}\right]^{\frac{1}{\gamma-1}}\{(\gamma-1)(1+\gamma-r)[\phi_M(\theta R-1)]+r[r(\gamma-1)+(\gamma+1)]\}.
\end{aligned}$$

Now we have

$$\frac{\partial \Phi}{\partial r} < 0 \Leftrightarrow \frac{(1+\gamma)^2[\phi(\theta R-1)]}{(\gamma-1)(1+\gamma-r)[\phi_M(\theta R-1)]+r[r(\gamma-1)+(\gamma+1)]} < \left[\frac{\phi_M(\theta R-1)-r}{\phi(\theta R-1)-r}\right]^{\frac{1}{\gamma-1}}.$$

Assumption 5.1 ensures the right-hand side of the inequality is bounded below by 1. A sufficient condition to ensure $\frac{\partial \Phi}{\partial r} < 0$ is

$$\frac{(1+\gamma)^2[\phi(\theta R-1)]}{(\gamma-1)(1+\gamma+r)} - \frac{r[r(\gamma-1)+(\gamma+1)]}{(\gamma-1)(1+\gamma-r)} < [\phi_M(\theta R-1)].$$

The above inequality says that if synergy benefits are sufficiently large under our simplifying assumptions, as the required return r rises, the merger portion of MB declines because the declines in the present value of a would-be merged bank exceed the cost savings from the reduction in required investments. Thus, under additional assumptions and sufficient conditions, the MB ratio declines in all states as the required return rises.

We note the net interest margin is independent of r, and with respect to the efficiency ratio, we have

$$\frac{\partial E}{\partial r} = \begin{cases} -\frac{1}{\alpha\phi_{i,j}\theta R} & \text{standalone} \\ -\frac{1}{\psi\phi_M\theta R} & \text{merged.} \end{cases}$$

We observe the efficiency ratio declines as the required returns rise. This suggests that the required return disciplines the efficiency ratio of banks.

Lastly, the inequality in Corollary 6.2 can be expressed as

$$\begin{aligned} s_{i_j,i'_{j'}} - X_{i,j} - X_{i',j'} < {} & \frac{1/2q_i(\theta_m)}{2G+1/2q_i(\theta_m)+1/2q_{i'}(\theta_m)}(s_{i_j,i'_j} - X_{i,j} - X_{i',j}) \\ & + \frac{1/2q_{i'}(\theta_m)}{2G+1/2q_i(\theta_m)+1/2q_{i'}(\theta_m)}(s_{i'_j,i'_{j'}} - X_{i,j'} - X_{i',j'}) \end{aligned}$$

Let us define the function

$$\begin{aligned} \Xi = {} & \frac{1/2q_i(\theta_m)}{2G+1/2q_i(\theta_m)+1/2q_{i'}(\theta_m)}(s_{i_j,i'_j} - X_{i,j} - X_{i',j}) \\ & + \frac{1/2q_{i'}(\theta_m)}{2G+1/2q_i(\theta_m)+1/2q_{i'}(\theta_m)}(s_{i_{j'},i'_{j'}} - X_{i,j'} - X_{i',j'}) \\ & - (s_{i_j,i'_{j'}} - X_{i,j} - X_{i',j'}). \end{aligned}$$

We observe the inequality satisfied whenever $\Xi > 0$. Similarly to before, how a rise in the required return impacts the likelihood of assortative matching occurring is determined by the sign of $\frac{\partial \Xi}{\partial r}$. Let us define the subparts of Ξ as

$$\begin{aligned}
\Lambda_i =& \frac{1/2q_i(\theta_m)}{2G + 1/2q_i(\theta_m) + 1/2q_{i'}(\theta_m)},\\
\Lambda_{i'} =& \frac{1/2q_{i'}(\theta_m)}{2G + 1/2q_i(\theta_m) + 1/2q_{i'}(\theta_m)},\\
\Phi_j =& s_{i_j,i'_j} - X_{i,j} - X_{i',j}\\
=& 2\left[\frac{\phi^j_M(\theta R-1)-r}{\psi}\right]^{\frac{1}{\psi-1}}\left[\frac{(\psi-1)\phi_M(\theta R-1)+(1-\psi)r}{\psi r}\right]\\
&-\left[\frac{\phi_{i,j}(\theta R-1)-r}{\alpha}\right]^{\frac{1}{\alpha-1}}\left[\frac{(1+\alpha)\phi_{i,j}(\theta R-1)-(1+\alpha)r}{\alpha r}\right]\\
&-\left[\frac{\phi_{i',j}(\theta R-1)-r}{\alpha}\right]^{\frac{1}{\alpha-1}}\left[\frac{(1+\alpha)\phi_{i',j}(\theta R-1)-(1+\alpha)r}{\alpha r}\right],\\
\Phi_{j'} =& s_{i_{j'},i'_{j'}} - X_{i,j'} - X_{i',j'},\\
\Phi_{j,j'} =& s_{i_j,i'_{j'}} - X_{i,j} - X_{i',j'}.
\end{aligned}$$

We observe $\Phi_j, \Phi_{j'}, \Phi_{j,j'}$ are identical with simply different synergy benefits let us suppress the market i notation and let Φ^j_M be the synergy benefits for a matched type j bank, let $\Phi^{j'}_M$ be the synergy benefits for a matched type j' bank and let $\Phi^{j,j'}_M$ be the synergy benefits for the matching of two different types of banks. We have

$$\frac{\partial \Xi}{\partial r} = \frac{\partial \Lambda_i}{\partial r}\Phi_j + \Lambda_i\frac{\partial \Phi_j}{\partial r} + \frac{\partial \Lambda_{i'}}{\partial r}\Phi_{j'} + \Lambda_{i'}\frac{\partial \Phi_{j'}}{\partial r} - \frac{\partial \Phi_{j,j'}}{\partial r}.$$

We have

$$\begin{aligned}
\frac{\partial \Lambda_i}{\partial r} =& -\frac{q_i(\theta_m)}{[2G + 1/2q_i(\theta_m) + 1/2q_{i'}(\theta_m)]^2}\left\{\frac{\lambda^{MP}\lambda^{NM}}{(\lambda^{NM}+r)^2}+1\right\} < 0,\\
\frac{\partial \Lambda_{i'}}{\partial r} =& -\frac{q_{i'}(\theta_m)}{[2G + 1/2q_i(\theta_m) + 1/2q_{i'}(\theta_m)]^2}\left\{\frac{\lambda^{MP}\lambda^{NM}}{(\lambda^{NM}+r)^2}+1\right\} < 0.
\end{aligned}$$

Under our simplifying assumptions, we have

$$\frac{\partial \Phi_j}{\partial r} = -\frac{2[(1+\gamma^2)\phi^j_M(\theta R-1)-(\gamma-1)r]}{\gamma(\gamma-1)r^2}\left[\frac{\phi^j_M(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}$$

$$
\begin{aligned}
&- \frac{2[(\gamma^2-1)\phi_j(\theta R-1)-(1+\gamma)r]}{\gamma(1-\gamma)r^2}\left[\frac{\phi_j(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}} < 0\\
\frac{\partial \Phi_{j'}}{\partial r} &= - \frac{2[(1+\gamma^2)\phi_M^{j'}(\theta R-1)-(\gamma-1)r]}{\gamma(\gamma-1)r^2}\left[\frac{\phi_M^{j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}\\
&- \frac{2[(\gamma^2-1)\phi_{j'}(\theta R-1)-(1+\gamma)r]}{\gamma(1-\gamma)r^2}\left[\frac{\phi_{j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}} < 0\\
\frac{\partial \Phi_{j,j'}}{\partial r} &= - \frac{2[(1+\gamma^2)\phi_M^{j,j'}(\theta R-1)-(\gamma-1)r]}{\gamma(\gamma-1)r^2}\left[\frac{\phi_M^{j,j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}\\
&- \frac{[(\gamma^2-1)\phi_j(\theta R-1)-(1+\gamma)r]}{\gamma(1-\gamma)r^2}\left[\frac{\phi_j(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}}\\
&- \frac{[(\gamma^2-1)\phi_{j'}(\theta R-1)-(1+\gamma)r]}{\gamma(1-\gamma)r^2}\left[\frac{\phi_{j'}(\theta R-1)-r}{\gamma}\right]^{\frac{1}{\gamma-1}} < 0
\end{aligned}
$$

We observe all signs are negative under the parameter assumptions $\gamma > 1$ and $r \in (0,1)$. A concern that may arise if the magnitude $\frac{\partial \Phi_{j,j'}}{\partial r}$ dominates the remainder terms. We observe that if synergy benefits ϕ_M^j and $\phi_M^{j'}$ are sufficiently high, then a rise in the required return lowers the likelihood of assortative matching. $\square$