# Strategic Bank Consolidations:
# Intangible Capital Channel [*]

Suleyman Gozen [†] David Hong [‡] Mehmet Furkan Karaca [§]

**Abstract**

This paper examines how internally generated intangible capital shapes merger patterns and post-merger performance in the U.S. banking sector. We construct a novel measure of intangible capital using granular regulatory expense data and quantify assortative matching between acquirers and targets. Employing a difference-in-differences design with propensity score matching, we causally show that higher assortative matching in intangible capital leads to significant improvements in post-merger bank performance. We complement the empirical analysis with a dynamic search-theoretic model of bank mergers, demonstrating that strategic complementarities in intangibles give rise to assortative matching equilibria. Our findings provide new insights into banking consolidation.

**Keywords**: Intangible Capital, Bank Mergers and Acquisitions, Assortative Matching, Bank Performance, Causal Analysis

**JEL Codes**: E22, E44, G21, G34

[*]The previously circulated title was *"Strategic Acquisitions Amongst Financiers in the Intangible Economy"*. We thank Arpad Abraham, Pierre Boyer, Se Kyu Choi, Jeanne Commoult, Pawel Doligalski, Nick Frazier, Luisa Fuster, Ruveyda Gozen, Paul Grout, Johan Hombert, Ali Hortacsu, Tai-Wei Hu, Jessica Jeffers, John Bailey Jones, Kei Kawakami, Timothy Kehoe, Nobuhiro Kiyotaki, Gizem Kutlu, Shuyun May Li, Georgios Manolis, Sergio Feijoo Moreira, Marco Pagano, Emmanouil Pyrgiotakis, Karl Schulz, Ekaterina Volkova, Luke Watson, Hakki Yazici, and Hanzhe Zhang as well as workshop/conference participants at Bristol Macro Brownbag, Essex Finance Center Conference in Banking and Finance, Financial Economics Meeting, Winter Workshop in Economics at Koc University, and 2024 Asia Meeting of the Econometric Society, East & Southeast Asia for helpful comments and suggestions. Computer programs to replicate the empirical/simulation analyses are available from the authors. All errors are our own.

[†]School of Economics, University of Bristol. 12 Priory Road, Bristol BS8 1TU, United Kingdom.
Email: suleyman.gozen@bristol.ac.uk.

[‡]School of Economics, The University of Edinburgh. 30 Buccleuch Place, Edinburgh EH8 9JTE, United Kingdom.
Email: dhong@ed.ac.uk.

[§]Essex Business School, University of Essex. Wivenhoe Park, Colchester CO4 3SQE, United Kingdom.
Email: m.f.karaca@essex.ac.uk.

# 1 Introduction

Over the past several decades, the United States banking sector has undergone significant consolidation, reducing the number of banks operating in 1985 from over 17,000 to fewer than 5,000 by 2020. Coincidentally, there has been a growing importance of intangible capital — including proprietary software, managerial expertise, organizational culture, and customer data — as a driver of value creation and business performance. While the existing literature has focused on the implications of intangible capital in non-financial sectors (Eisfeldt and Papanikolaou, 2013, among others) and in particular how it shapes mergers and acquisitions (M&As) and ex-post performance (Li et al., 2018, among others), much less is known about how intangible capital affects bank consolidation patterns and its post-merger performance. We address several questions: Through which channels does intangible capital influence bank M&A strategies? What are the key characteristics of bank M&A transactions when analyzed through the dimension of intangible capital? How does intangible capital affect bank post-merger performance? We develop both an empirical and a theoretical framework to provide a comprehensive analysis of the impact of intangible capital in shaping bank M&A dynamics and outcomes. To the best of our knowledge, our paper is one of the first studies to provide a deep understanding of the role of intangible capital in financial consolidations.[1]

Using various databases, including U.S. Call Reports and data on bank mergers and acquisitions, we construct a measure of internally generated intangible capital based on non-interest expense items that most plausibly reflect investment in organizational and knowledge-based capabilities. We then define a metric of assortative matching, which enables us to assess the degree of ex ante alignment and its implications for merger success. We document several stylized facts: First, we show that bank intangible capital has grown substantially relative to traditional balance sheet items such as loans, assets, and deposits, reflecting a structural shift in how banks generate value. Second, we find that higher intangible intensity is positively associated with key bank performance indicators, including Net Interest Margin (NIM), Return on Loans (ROL), and loan-to-asset ratios. Third, we provide robust evidence of assortative matching in bank M&As: pairwise comparisons and regression estimates show that banks with similar characteristics—particularly in intangible capital—are more likely to merge. This pattern holds consistently over time and is not merely a product of macroeconomic cycles or industry-specific shocks. Comparisons with hypothetical merger pairs further suggest that realized mergers exhibit systematically stronger assortative matching in intangible capital than random matches.

Furthermore, we conduct a causal analysis using a difference-in-differences framework, which is con-

[1] We use the terms "consolidations" and "M&As" interchangeably.

sistent with the related literature. A key challenge for causal identification is the potential selection bias of acquirers and targets in bank M&As, which may be endogenous to our dependent variables. To address these endogeneity concerns, we adopt a quasi-natural experimental approach. Specifically, we focus on a treated group consisting of acquirer banks involved in successful M&A deals and a control group comprised of acquirer banks whose M&A deals were terminated or withdrawn for reasons unrelated to bank performance and/or intangible capital. Consequently, our identification strategy estimates the causal impact of intangible capital on bank performance metrics by comparing successful acquirers to a control group of comparable acquirers whose M&As did not proceed due to exogenous factors.

Incorporating propensity score matching to compare similar units, our causal results confirm that the positive effects of bank M&As are concentrated among high-assortative matches to intangible capital. For these deals, we estimate an average post-merger increase of 0.2 percentage points in NIM, 0.4 percentage points in ROL, and 6 percentage points in Operating Efficiency Growth relative to the control group. In contrast, low-assortative matches do not exhibit statistically significant improvements. Our findings extend insights from non-financial sectors by demonstrating the relevance of intangible capital in financial sector consolidations and emphasizing the role of assortative matching in shaping M&A dynamics and post-merger outcomes. In particular, we identify a novel channel through which heterogeneity in bank M&A outcomes arises from the alignment of intangible capital, which serves as a key determinant of synergy gains.

Our key mechanism is that the complementarity of intangible capital — proxied through organizational and knowledge-based expense categories — shapes both the selection patterns and ex-post outcomes of bank consolidation. These complementarities operate through multiple interrelated channels. First, a bank that acquires another with complementary internal systems, such as loan monitoring, compliance, or HR platforms, can integrate its operations more seamlessly, thereby reducing post-merger friction. Second, the merger may enhance the joint entity's screening and lending capacity by pooling know-how embedded in customer analytics, branch operations, and credit evaluation infrastructure. Third, the broader knowledge base — including internal training systems, IT routines, and customer service practices — can scale more effectively within a merged institution. These complementarities suggest that assortative matching in internally generated intangible capital is a key determinant of both the intensive margin of M&A behavior — specifically, the choice of merger partners — and the realized post-merger gains.

Lastly, we augment a continuous-time Diamond-Mortensen-Pissarides search model of Rhodes-Kropf and Robinson (2008) for financial intermediaries. Parsimoniously, banks face constant returns to scale in their loan portfolios, subject to a convex monitoring (or screening) cost that is endogenous to their intangible capital. Banks face an exogenous discovery shock with the same reasoning as Gort (1969) and randomly match. The equilibrium patterns of bank M&As are endogenous, with banks rationally choosing to continue searching after an initial mismatch. Consistent with our empirical findings, we focus on the case where synergy benefits exhibit strategic complementarity (i.e., the supermodularity condition holds) and establish an assortative matching equilibrium. Agnostically, we do not commit to ex-post efficiency gains and allow for flexible generalizations of ex-post changes in the convexity of monitoring and screening costs.

We employ counterfactual simulations to examine the impact of regulatory policies on assortative matching and post-merger efficiency. As a thought experiment, suppose the regulator can alter the exogenous probability of banks entering a state where they can merge.[2] We simulate an analytical characterization capturing the likelihood of assortative matching calibrated to empirical moments and find a threshold where stricter regulations can break the equilibrium. The intuition is that banks internalize the costliness of re-searching; thus, a sufficiently low probability results in banks rationally merging with mismatched partners.

Next, we simulate post-merger efficiency gains under assortative matching. We arrive at an analytical characterization of relative efficiency that is a function of (i) the ratio of convexity and (ii) synergy. Our simulation, calibrated to empirical moments, shows a region of convexity change and synergy that leads to ex-post bank efficiency losses. The intuition is that banks rationally find it profitable to merge with similar banks because the revenue motive exceeds the rise in marginal operating costs. From a regulator's perspective, permitting such bank consolidations may be welfare-reducing. Thus, our simulation provides a conceptual litmus test for permitting or rejecting bank merger requests, showing that assortative matching is not a carte blanche guarantee of efficiency gains. Both simulations offer valuable insights into how regulatory frameworks influence merger patterns and shape the overall efficiency of the banking sector.

As policymakers increasingly revisit the regulatory framework governing bank mergers, our paper offers important insights for ongoing debates on merger oversight and the conditions under which consolidation creates value. Recent interagency coordination efforts by the Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency, and Department of Justice, 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. Our findings suggest that strategic M&A decisions leveraging intangible capital can potentially deliver long-term benefits to the financial system. These benefits may also help mitigate concerns about reduced consumer choice or increased risks of market concentration associated with M&As.

[2] We do not consider regulatory objectives related to market power or financial stability, as these are beyond the scope of our framework.

**Related Literature** Our paper relates to several branches in the literature. The importance of intangible capital by financial intermediaries has been discussed by Nash and Sinkey Jr (1997); Nagar and Rajan (2005); Calomiris and Nissim (2014). Nash and Sinkey Jr (1997) uncover intangible assets comprised of credit card relationships are a driver of premiums in the resale market for credit card receivables. While Nagar and Rajan (2005) find customer relationship assets are better predictors of future profitability for banks. Similarly, Calomiris and Nissim (2014) discovered the sharp decline in bank market-to-book ratios during The Global Financial Crisis was primarily due to a decrease in customer relationship assets rather than delayed loss recognition. These studies suggest that the capitalization of customer-specific intangibles captures the competitive advantages of relationship lending.

Our study uncovers that intangible capital are essential to understanding U.S. financial consolidation patterns. Naturally, our findings relate to the literature on the determinants of bank mergers and acquisitions, including bank fundamentals (Focarelli et al., 2002; Alessandrini et al., 2008), market expansion (Beccalli and Frantz, 2013; Levine et al., 2020), and the impact of regulations (Carletti et al., 2007; Bindal et al., 2020). Both Focarelli et al. (2002) and Alessandrini et al. (2008) investigate the Italian banking sector and uncover the aim of bank consolidations is to boost profitability by restructuring loan portfolios and eliminate unprofitable activities occurring in acquired banks. Both papers suggest consolidation patterns may reflect strategic substitutability in Italy while we uncover strategic complementarity among U.S. banks. Beccalli and Frantz (2013) find larger banks with high ex-ante cost-efficiency and strong growth history were more likely to be acquiring entities in M&A deals. While Levine et al. (2020) find banks with more significant overlap in geographic locations of their bank branches were more likely to consolidate. Our findings complement these two papers by uncovering an assortative matching pattern in bank M&A activities. This suggests banks of similar characteristics (e.g., size, intangible capital) are more likely to consolidate. Carletti et al. (2007) find stricter banking regulations in Europe decrease the likelihood of M&As among European banks. While Bindal et al. (2020) find U.S. banks below the size threshold of the 2010 Dodd-Frank Act were more likely to be acquirers. Our theoretical simulations highlight how stricter regulations on bank M&A activity can disrupt the assortative matching equilibrium.

We also find that assortative matching in intangible capital (i.e., a close ex-ante level of intangible capital between the acquirer and the acquiree) drives ex-post outcomes for consolidated banks. Rhoades (1993) find for the period between 1981 and 1986, horizontal bank mergers did not lead to improved efficiency gains as predicted. Cornett et al. (2006) find a significant increase in the industry-adjusted operating performance of merged banks, with greater performance gains for consolidations between large banks than small banks. Akkus et al. (2016) find the value-creation of bank M&A deals is due to improved cost-efficiencies and network effects. Our findings align with Rhoades (1993) and Akkus et al. (2016) with nil ex-post bank performance for M&As where distance in ex-ante levels of intangible assets was greater than the sample median. For a more thorough survey, see DeYoung et al. (2009).

**Layout** We organize the paper as follows: Section 2 introduces the databases used to investigate intangible capital in the banking industry and assortative matching in bank M&As. Section 3 provides empirical facts on intangible capital and assortative matching in banking. Section 4 presents the causal analysis framework and evidence on the role of intangible capital synergy in post-merger bank performance. Section 5 summarizes our robustness checks. Section 6 introduces the model framework. Section 7 characterizes the model's equilibrium and discusses its implications. Finally, Section 8 concludes by summarizing the key results and discussing regulation-related perspectives.

## 2 Data and Measurement

This section describes the different data sources used in our 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 with a more extended time period coverage (1976-2020) than the new Call Reports dataset (2001-onwards). In addition, we obtained 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 fundamentals 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. Following conventions in the literature, and particularly the variable definitions in Cornett et al. (2006), we use a set of bank-level indicators, some of which are listed in Table A.1. Table A.2 presents the summary statistics for selected bank-level quarterly variables from U.S. Bank 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: We only consider (i) commercial bank (*charter type* $= 200$) M&A transactions; (ii) 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) 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 1,156 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.

For our causal analysis, we construct a control group using bank M&A deals that are either terminated or withdrawn. 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 and unique identifiers for both acquirer and target entities. We 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 in our control group consists of (i) 119 terminated bank M&A deals and (ii) 156 withdrawn bank M&A deals.

**Bank Intangible Capital** Using granular data from U.S. Call Reports, we construct a forward-looking proxy for intangible capital tailored to the banking context. Our approach focuses on detailed subcomponents of ”other noninterest expenses” that plausibly reflect investments in software, customer relationships, human capital, and internal processes. These include line items such as data processing, marketing, telecommunications, and itemized discretionary expenses flagged through keyword analysis of textual descriptions. To construct a quarterly stock measure, we apply a perpetual inventory method and validate our resulting measure by comparing it to both externally reported intangible assets and the bank-level IT expense data provided by Modi et al. (2022). This methodology allows us to capture a key but often unobserved component of bank capabilities and strategic value. Additional details and validation exercises are provided in Appendix Section C. From this point onward, we refer to our constructed measure of internally generated intangible capital simply as intangible capital.

# 3 Stylized Facts

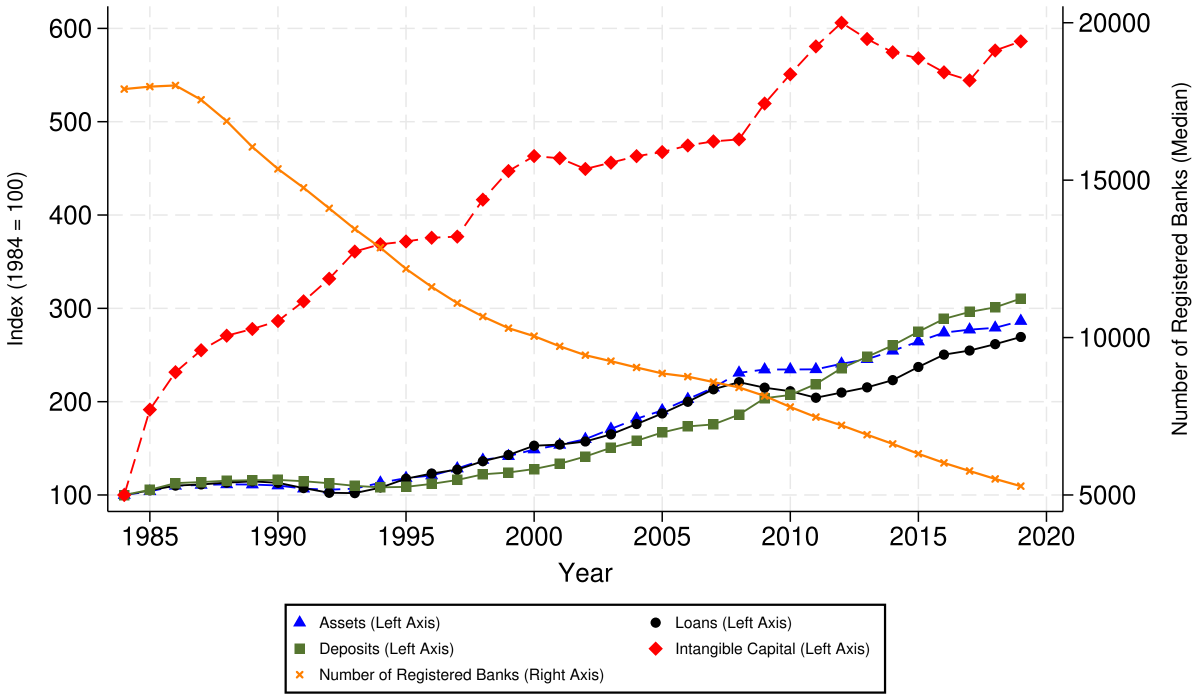
We provide stylized facts and empirical evidence on the role of intangible capital in bank M&A patterns. First, we document several key facts regarding the increasing share and importance of intangible capital in the U.S. banking industry. Second, we provide empirical evidence of assortative matching in bank M&As along the dimensions of key balance-sheet variables and intangible capital.

## 3.1 Intangible Capital in Banking

Utilizing quarterly aggregate time-series statistics from the U.S. Federal Deposit Insurance Corporation and the U.S. Call Reports, Figure 1 shows that while the number of registered banks steadily declines—reflecting ongoing consolidation in the industry—measures of balance sheet size and capital components show diverging dynamics. When normalized to 100 at the beginning of the sample, intangible capital grows markedly faster than traditional balance sheet aggregates such as total assets, loans, and deposits. This divergence suggests the increasing importance of intangible capital in banking, indicating a structural shift in how banks accumulate value and maintain competitive advantage over time.

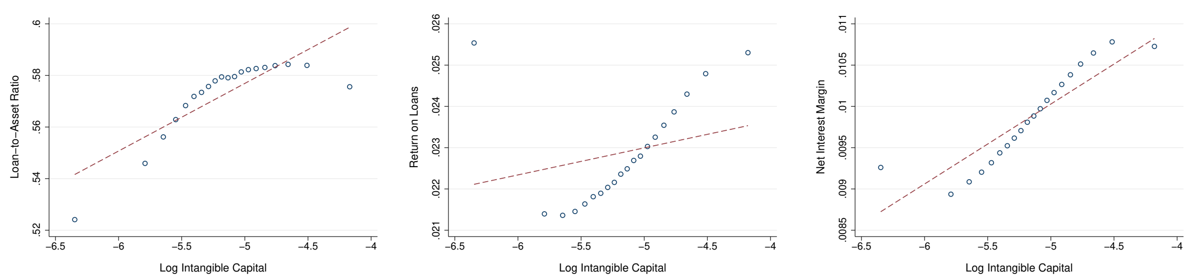
Using the constructed measure of intangible capital from U.S. Call Reports, Figure 2 presents binned scatterplots examining the relationship between intangible capital and key bank performance metrics using quarterly-level data. Each panel plots a different outcome—loan-to-asset ratio, return on loans (ROL), and net interest margin (NIM)—against the log of intangible capital normalized by total assets. Across all three panels, we observe positive correlations, suggesting that banks with higher intangible intensity tend to perform better along multiple dimensions. These patterns provide preliminary evidence that intangible capital may play a significant role in shaping bank performance. Motivated by these findings, the remainder of the paper investigates this relationship more systematically in the context of mergers and acquisitions.

Figure 1: Number of Registered Banks, Intangible Capital, and Balance Sheet Variables




Note: This figure plots the number of registered banks (right axis) and index values of total assets, net loans, deposits, and intangible capital (left axis). All index series are normalized to 100 at the start of the sample period.

Figure 2: Binscatter Plots: Bank Performance and Intangible Capital




(a) Loan-to-Asset Ratio

(b) Return on Loans

(c) Net Interest Margin

Note: This figure presents binned scatterplots of the log of intangible capital normalized by total assets against, respectively, the loan-to-asset ratio, return on loans (ROL), and net interest margin (NIM), using bank-quarter level data. Each panel uses 20 quantile bins of the independent variable.

Table 1 shows suggestive regression evidence that intangible capital is positively associated with key bank performance metrics. Higher levels of intangible capital are associated with increases in Net Interest

Margin (NIM), Return on Loans (ROL), and the Loan-to-Asset ratio. These patterns indicate that intangible capital may play a meaningful role in shaping banks' lending behavior and profitability, even though the analysis does not establish causality. Motivated by these facts, we next provide causal evidence on the role of intangible capital by exploiting variation generated through bank mergers and acquisitions.

Table 1: Regression Estimates: Bank Performance and Intangible Capital

| | Net Interest Margin | | Return on Loans | | Loan-to-Asset Ratio | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log Intangible Capital | 0.0016*** | 0.0011*** | 0.0068*** | 0.012** | 0.038*** | 0.025*** |
| | (0.00009) | (0.0001) | (0.003) | (0.008) | (0.002) | (0.001) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | No | Yes | No | Yes | No | Yes |
| BHC FE | No | Yes | No | Yes | No | Yes |
| $R^2$ | 0.07 | 0.26 | 0.0008 | 0.01 | 0.19 | 0.72 |
| N | 1268913 | 1268658 | 1265369 | 1265118 | 1272198 | 1271944 |

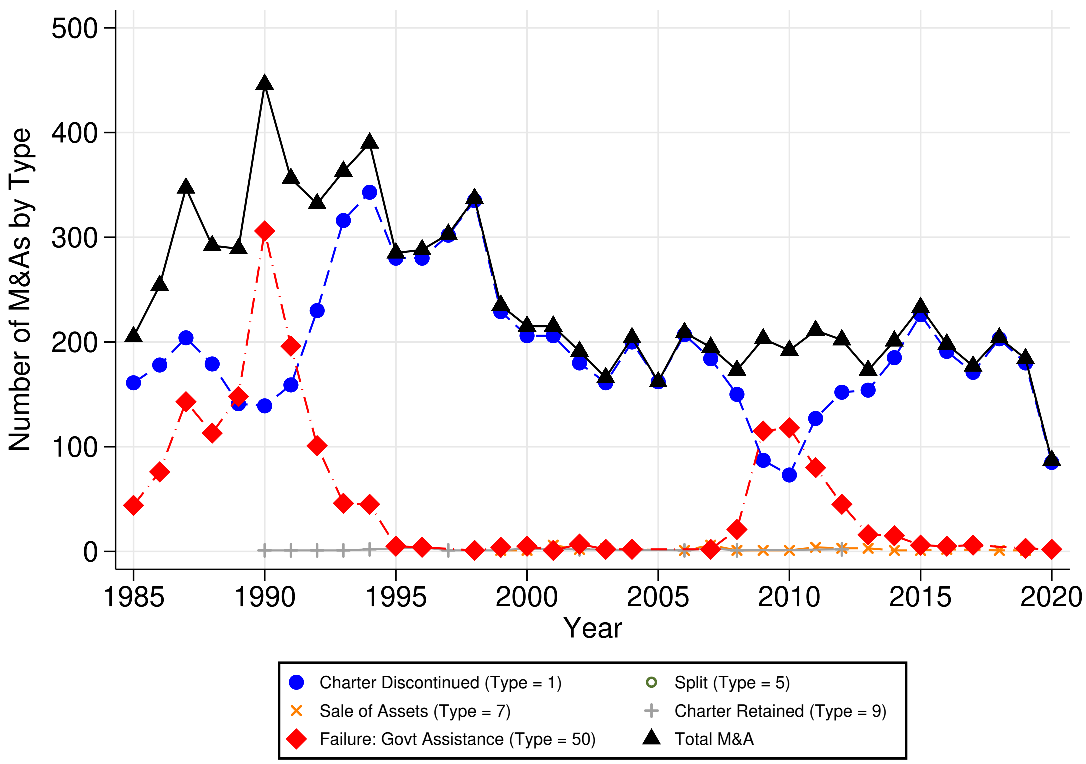
Note: This table reports panel regression estimates of the relationship between banks' logarithm of intangible capital (normalized by total assets) and several key bank performance indicators: Net Interest Margin (NIM), Return on Loans (ROL), and the Loan-to-Asset ratio. Control variables are bank-level logarithm of assets, deposits, equity, return on assets, and loan loss provision ratio. Standard errors (in parentheses) are clustered at the bank level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

### 3.2 Observations 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. 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*".

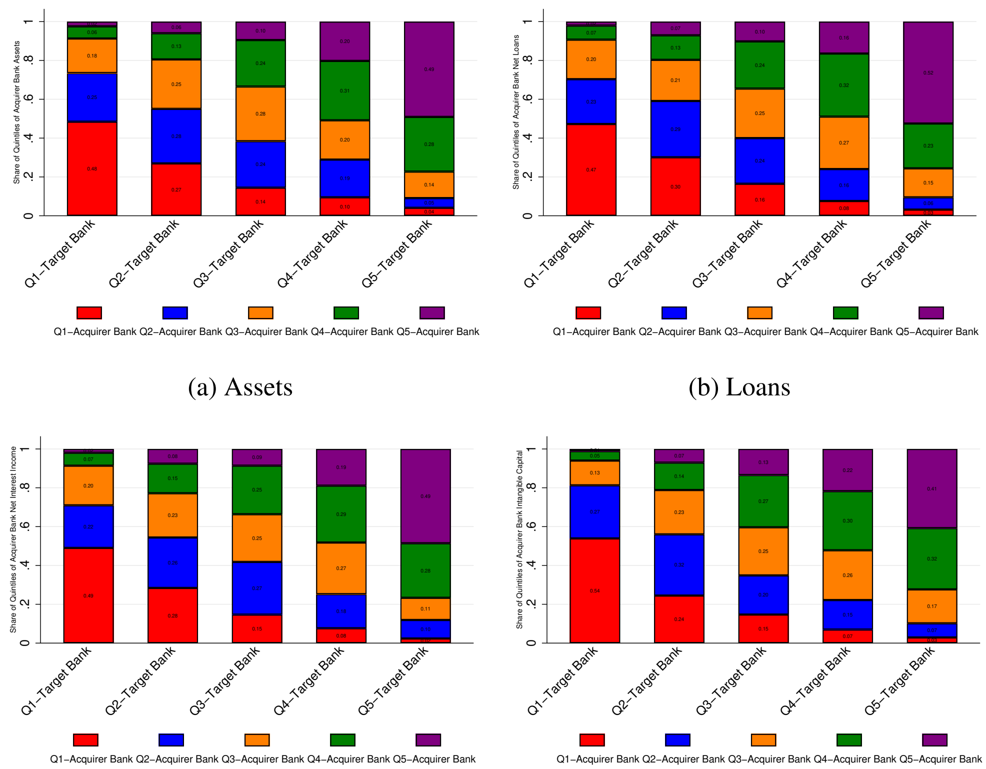
Figure 3: Bank M&A Types




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.

**Assortative Matching in Bank Characteristics** After merging the U.S. Call Reports with bank-level M&A data, we can observe the pairwise information of various bank characteristics (acquirer bank - acquiree/target bank pair). 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 48%, 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 49% 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 capital, as documented in Figures 4b, 4c, and 4d, respectively. In other words, acquirer banks with higher (lower) total loans, net interest income, and intangible capital are more likely to merge with target banks with higher (lower) total loans, net interest income, and intangible capital, respectively. Therefore, we observe suggestive evidence of strong assortative matching between the two sides of M&As.

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




(a) Assets

(b) Loans

(c) Net Interest Income

(d) Intangible Capital

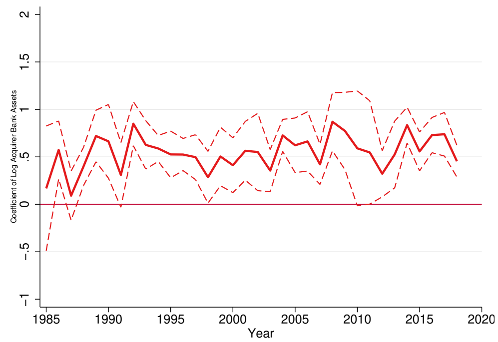
Note: This figure shows the share of each matched quintile of target-bank and acquirer-bank. Quintiles are constructed based on the total assets, net loans, net interest income, and intangible capital within each year, respectively.

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

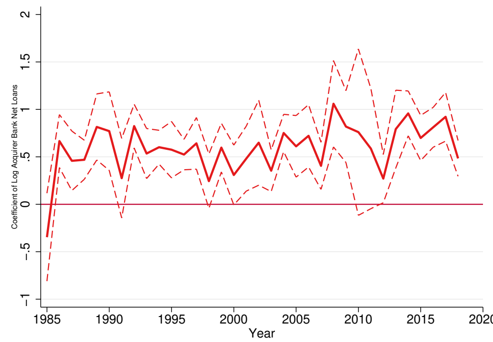
$$target_{it} = \beta_{0t} + \beta_{1t} acquirer_{it} + u_t + \epsilon_{it} \tag{1}$$

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 capital, 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 $\beta_{1t}$, indicating the time-varying degree of assortative matching between target banks and acquirer banks.

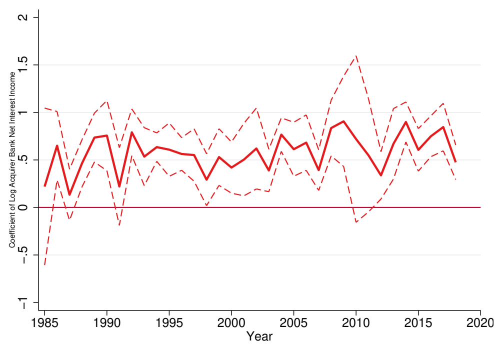
Figure 5: Assortative Matching - Regression Coefficient



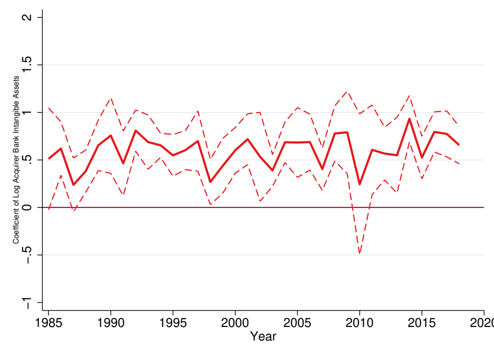

(a) Assets




(b) Loans




(c) Net Interest Income




(d) Intangible Capital

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.

Figure 5 plots the regression estimate of $\beta_{1t}$ over time for different selected variables of bank characteristics. We observe a common pattern in all specifications: 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.

### 3.3 Empirical Evidence on Assortative Matching in Bank M&As

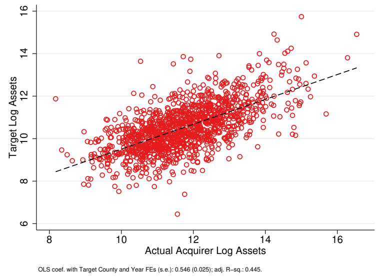
We construct hypothetical mergers that could have occurred but did not and compare them with actual mergers. In essence, we juxtapose actual bank mergers with randomly paired non-merging banks. For each acquirer and target bank in our sample, we substitute them with banks that did not engage in a merger within the same year. 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 twofold: (i) If assortative matching is systematically present in bank M&A transactions, a significant relationship should be observed when compared to random pairings; (ii) Given a significant relationship is observed, how bank characteristics shape the direction of assortative matching towards strategic complementarity or strategic substitutability can be uncovered.

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.

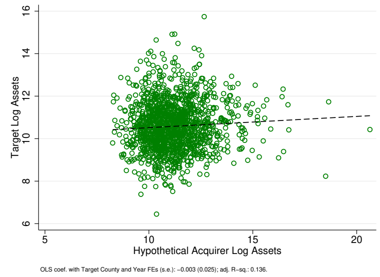
Table A.5 compares actual and hypothetical mergers using summary statistics on the actual and the square of differences of the logarithm of assets, loans, and intangible capital for acquirer-target merger pairs. The first row of each subgroup in the table reveals that hypothetical mergers exhibit a lower mean spread than actual mergers, with this difference being highly statistically significant. The second row of each subgroup explains this observation by reporting the square values of the acquirer-target selected metrics, which generally show a significant difference between actual and hypothetical merger pairs. This difference is relatively smaller for actual merger pairs. Our set of findings supports the existence of assortative matching, as the random sampling method produces many more high-buy-low transactions than what is observed in the actual data.

Table 2 conducts a Probit analysis comparing actual mergers with a set of hypothetical bank pairings to assess whether similarity in key characteristics predicts merger likelihood. Specifically, we examine whether the squared differences in log loans, net interest income (NII), and intangible capital between potential acquirer-target pairs affect the probability of an actual merger. Across all specifications, the coefficient on the intangible capital difference is consistently negative and statistically significant, indicating that banks with more similar levels of intangible capital are significantly more likely to merge. In contrast, similarity in loans or NII does not consistently predict merger realization once all variables are included in the same regression. These results emphasize the centrality of intangible capital in M&A partner selection and suggest that intangible alignment—not merely conventional balance sheet similarity—plays a distinctive and economically meaningful role in driving assortative matching in bank mergers.

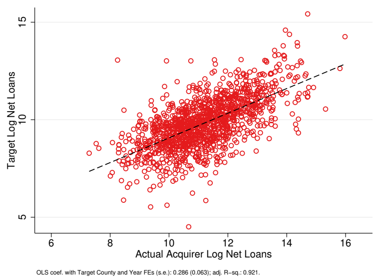
Figure 6: Actual and Hypothetical Mergers



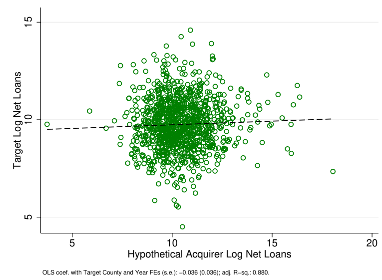

(a) Actual - Assets



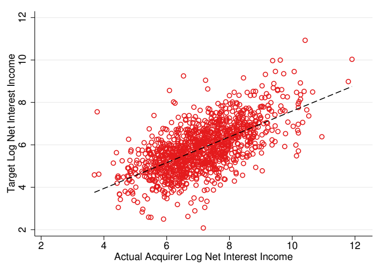

(b) Hypothetical - Assets



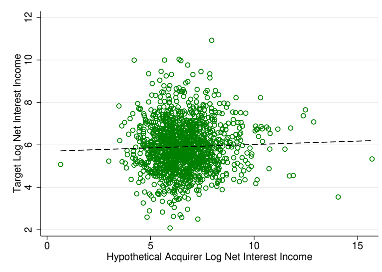

(c) Actual - Loans



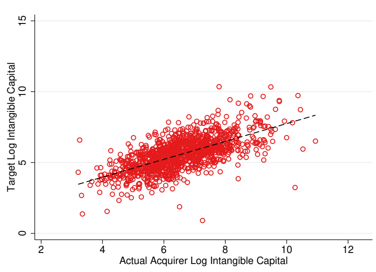

(d) Hypothetical - Loans



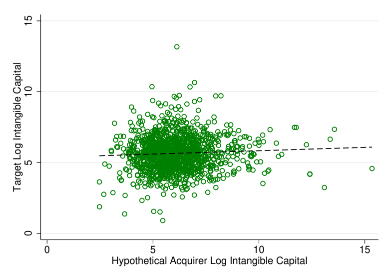

(e) Actual - Net Interest Income




(f) Hypothetical - Net Interest Income




(g) Actual - Intangible Capital




(h) Hypothetical - Intangible Capital

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.

Table 2: Probit Estimates - Actual and Hypothetical Mergers

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| (Acq. (Log Loans) - Targ. (Log Loans))$^2$ | -0.008 | -0.01 | | | | | -0.0008 |
| | (0.008) | (0.01) | | | | | (0.01) |
| (Acq. (Log NII) - Targ. (Log NII))$^2$ | | | -0.013 | -0.016 | | | 0.02 |
| | | | (0.009) | (0.01) | | | (0.019) |
| (Acq. (Log Intangible Capital) - Targ. (Log Intangible Capital))$^2$ | | | | | -0.06$^{**}$ | -0.08$^{***}$ | -0.11$^{***}$ |
| | | | | | (0.02) | (0.02) | (0.02) |
| 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 | 2272 | 1947 | 2442 | 2436 | 2469 | 2463 | 1735 |

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 the square of differences of i) the logarithm of loans, ii) the logarithm of net interest income (NII), and iii) the logarithm of intangible capital in merger pairs. We control the measure of assortative matching in total assets. Standard errors (in parentheses) are clustered at the target bank county-level. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

# 4 Causal Analysis

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

**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 variables. 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 capital targeted in such deals. Consequently, our identification strategy estimates the impact of intangible capital on acquirer bank performance 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 capital 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.[3] A letter[4] 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. 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[5] 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 bold 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 exclude those for which we can identify mentions of bank performance or intangible capital that may have contributed to the termination, as illustrated in the passage above. One potential concern is that the information set between acquirer and target banks may change after the deal is initiated, and hence terminated or withdrawn deals might result from changes in information. However, we argue that if there is a change in the information set, it would be reflected in deal summaries or other resources we check to refine our control group. Therefore, our approach

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

[4]The letter can be found here.

[5]The full article can be found here.

provides a sample of terminated or withdrawn deals that failed for reasons unrelated to the performance or intangible capital of the 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.

**Propensity Score Matching** 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 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 logarithm of assets, logarithm of deposits, logarithm of equity, return on equity, capital to assets ratio, loans to deposits ratio, asset growth rate, loan growth rate, deposit growth rate, return on assets, service charges to assets ratio, trading revenue to assets ratio, interest and dividend income on securities to assets ratio, and core deposits to assets ratio 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. Table 3 shows the results of the balance test between the selected variables of the treated and control groups in our sample after propensity score matching. We observe that none of the mean differences between the groups are statistically significant at the 5% significance level, which supports our argument that we are comparing banks with similar characteristics between the treated and control groups using propensity score matching.

**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 variables during the pre-merger period without treatment. Therefore, the assumption is that the trends in outcome variables between these two groups were parallel before the M&A event. This assumption ensures that any post-merger differences in net interest margin, return on loans, 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 dependent variables 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.

Table 3: Balance Test Between Treated and Control Groups

| Variable | Treated Group Mean | Control Group Mean | T-statistic | P-value |
|---|---|---|---|---|
| Log Loans | -0.439 | -0.460 | 0.957 | 0.339 |
| | (0.303) | (0.204) | | |
| | N = 1,575 | N = 1,248 | | |
| Log Deposits | -0.217 | -0.221 | 0.461 | 0.645 |
| | (0.172) | (0.119) | | |
| | N = 1,575 | N = 1,248 | | |
| Return on Equity | 0.030 | 0.022 | 0.465 | 0.642 |
| | (0.361) | (0.060) | | |
| | N = 1,582 | N = 1,248 | | |
| Liquidity Ratio | 0.270 | 0.270 | 0.052 | 0.959 |
| | (0.389) | (0.121) | | |
| | N = 1,582 | N = 1,248 | | |
| Loan Loss Provision Ratio | 0.0027 | 0.0016 | 1.463 | 0.144 |
| | (0.0138) | (0.0042) | | |
| | N = 1,582 | N = 1,248 | | |
| Capital Adequacy Ratio | 0.108 | 0.096 | 0.891 | 0.373 |
| | (0.237) | (0.030) | | |
| | N = 1,582 | N = 1,248 | | |

Note: This table presents the balance test between the selected variables of the treated and control groups in our sample after propensity score matching. The means are reported rounded to three decimal places in the table. Log variables are normalized by total assets. Ratio variables are defined as in Table A.1. Standard deviations are reported in parentheses, and sample sizes (N) are reported for each group.

**Sample Selection and Measures** We apply several sampling procedures to robustly define the treated and control groups in our difference-in-differences (DiD) causal inference design. First, since the unit of observation in terminated and withdrawn M&A deals is primarily at the bank holding company (BHC) level, we also measure our key variables of interest at this level in completed (successful) M&A deals. Second, we aggregate balance sheet and income statement variables from affected commercial bank subsidiaries involved in the transaction up to the BHC level. This aggregation strategy mitigates potential contamination from unrelated subsidiaries within the same BHC that were not involved in the M&A transaction. By focusing only on directly affected entities, we ensure that our treatment measure reflects the strategic and operational impact of the merger itself, rather than other ongoing activities within the BHC.

Third, we exclude all banks involved in M&A transactions where the charter outcome is not identified as either discontinued or retained. Transactions with other transformation codes often reflect partial integrations, branch sales, or internal restructuring events that do not produce clean acquirer–target dynamics, and including them risks misclassifying the merger structure. In addition, we drop any transactions in which the acquirer and target share the same BHC identifier, as these typically represent intra-group reorganizations rather than genuine external acquisitions. These restrictions allow us to focus exclusively on clear, arm's-length mergers and ensure that treatment status reflects substantive institutional changes rather than administrative restructuring.

Fourth, we exclude BHCs that appear in both completed and terminated/withdrawn M&A deals within a three-year window around the M&A year, ensuring that each BHC is assigned exclusively to either the treatment or control group, but not both. Finally, we exclude terminated and withdrawn M&A transactions if a bank is involved in multiple such deals within a five-year window. Overlapping transactions make it difficult to isolate the effects of any single deal and may reflect strategic behavior unrelated to a specific merger attempt. Dropping these cases helps ensure that each failed deal in our sample represents a distinct and interpretable shock to merger intentions.

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. 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 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. 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 1,116 unique acquirer bank holding companies in the treated group and 149 unique acquirer bank holding companies in the control group, totaling 13,533 bank-year observations.

**Causal Framework** To estimate the effect of bank mergers on performance, and to evaluate how this effect varies with the degree of assortative matching in intangible capital, we estimate the following difference-in-differences specification:

$$Y_{it} = \beta_1 \text{Post}_t \times \text{Treated}_i + \beta_2 \text{Post}_t \times \text{Treated}_i \times \text{HighAssort}_i$$

$$+ X'_{it-1}\gamma + \lambda_t + \theta_s + \mu_i + \delta_d + \varepsilon_{it} \tag{2}$$

where $Y_{it}$ denotes the performance outcome for bank $i$ in year $t$, which includes Net Interest Margin (NIM), Return on Loans (ROL), and Operating Efficiency Growth. The variable $\text{Post}_t$ is an indicator equal to one for the post-merger period, and $\text{Treated}_i$ equals one for acquirer banks in completed M&A deals. The interaction term $\text{Post}_t \times \text{Treated}_i$ captures the average treatment effect of mergers. To evaluate the role of assortative matching, we include a triple interaction term $\text{Post}_t \times \text{Treated}_i \times \text{HighAssort}_i$, where $\text{HighAssort}_i$ is an indicator equal to one if the acquirer-target pair ranks below the median in assortative matching in intangible capital.

The vector $X_{it-1}$ includes lagged control variables: log total assets, return on equity, total capital-to-asset ratio, loan-to-deposit ratio, and growth rates of total assets, loans, and deposits. All specifications include year fixed effects ($\lambda_t$), state fixed effects ($\theta_s$), and, in some specifications, bank holding company fixed effects ($\mu_i$) and deal (treatment status) fixed effects ($\delta_d$) which control for time-invariant heterogeneity across treated units and account for baseline differences in the nature or scale of mergers (e.g., size of the target, or geographic scope) that may be correlated with both assortative matching and performance outcomes. The error term $\varepsilon_{it}$ is clustered at the bank holding company level. The coefficient $\beta_1$ captures the average post-merger effect, while $\beta_2$ identifies whether this effect is amplified among mergers with stronger intangible capital matching.

We also explore the heterogeneous dynamic responses of acquirer banks that exhibit varying degrees of assortative matching in intangible capital. This investigation is crucial for understanding how the assortative matching in intangible capital 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 net interest margin, return on loans, and annual operating efficiency growth, based on the following framework:

$$Y_{it} = \sum_{k=-5}^{+5} \beta_k (\mathbb{1}\{\text{k Years to M\&A}\} \times \text{Treated}_i) + \Gamma X_{it-1} + \lambda_t + \theta_s + \mu_i + \delta_d + \varepsilon_{it} \tag{3}$$

where the subscripts $i$ and $t$ index the acquirer bank holding company and year, respectively. The dependent variables are Net Interest Margin (NIM), Return on Loans (ROL), and Operating Efficiency Growth. $\mathbb{1}\{k \text{ Years to M\&A}\}$ is an indicator function equal to 1 if the difference between year $t$ and the year of the M&A event is $k$, where $k \in [-5, 5]$. $\text{Treated}_i$ is a dummy variable equal to 1 if bank holding company $i$ is involved in a successful M&A deal, and 0 if it is part of the control group (e.g., associated with withdrawn or terminated deals). All other variables are as defined in Equation (2).

**Causal Estimates** Table 4 presents Difference-in-Differences (DiD) estimates, with a focus on how assortative matching based on intangible capital shapes post-merger effects. The baseline treatment effect (*Post* $\times$ *Treated*) is negative or insignificant across almost all outcomes, suggesting that M&As, on average, do not lead to immediate improvements in Net Interest Margin (NIM), Return on Loans (ROL), or Operating Efficiency Growth. However, the triple interaction term (*Post* $\times$ *Treated* $\times$ *Higher Assortative*) is positive and statistically significant in several specifications, particularly in columns (3), (6), and (9), indicating that mergers involving more similar (i.e., more assortative) pairs in terms of intangible capital are associated with improved performance. The coefficient on *Post* $\times$ *Treated* $\times$ *HighAssort* implies that, relative to other M&As, banks in high-assortative matches experienced a 0.3 percentage point higher Net Interest Margin (NIM), a 0.7 percentage point higher Return on Loans (ROL), and a 6 percentage point greater improvement in Operating Efficiency Growth after the merger.

Table 4: DiD Results

| | Net Interest Margin | | | Return on Loans | | | Oper. Eff. Growth | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Post $\times$ Treated | -0.00052 | -0.00016 | -0.002*** | -0.00037 | 0.00048 | -0.0026* | 0.0023 | 0.0079 | -0.039 |
| | (0.00068) | (0.00064) | (0.0007) | (0.0012) | (0.0012) | (0.0014) | (0.012) | (0.014) | (0.031) |
| Post $\times$ Treated $\times$ HighAssort | | | 0.0037*** | | | 0.0075*** | | | 0.069** |
| | | | (0.0013) | | | (0.0026) | | | (0.034) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Deal FE | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| BHC FE | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| $R^2$ | 0.34 | 0.66 | 0.75 | 0.39 | 0.62 | 0.65 | 0.27 | 0.31 | 0.29 |
| Observation | 2047 | 2045 | 861 | 2044 | 2042 | 857 | 2017 | 2014 | 844 |

This table reports Difference-in-Differences (DiD) estimates of the effect of bank M&As on bank performance, with a particular focus on the role of assortative matching. The variable *Post* $\times$ *Treated* captures the average treatment effect of M&As, while *Post* $\times$ *Treated* $\times$ *High Assortative* captures the additional effect for merger pairs with higher assortative matching in intangible capital. Outcome variables include Net Interest Margin (NIM), Return on Loans (ROL), and Operating Efficiency Growth. Control variables are one-year lagged log total assets, return on equity, total capital-to-asset ratio, loan-to-deposit ratio, and the growth rates of assets, loans, and deposits. Standard errors (in parentheses) are clustered at the bank holding company level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Figure 7 illustrates the dynamic causal impact of bank M&As on three key performance outcomes: Net Interest Margin (NIM), Return on Loans (ROL), and annual growth in operating efficiency. To isolate the role of intangible capital in these effects, we divide the treated group into two subgroups: one for acquirer banks with higher assortative matching (i.e., below the median the square of difference in intangible capital between acquirer and target banks) and another for those with lower assortative matching (i.e., above the median). As discussed in the empirical facts section, smaller differences imply greater similarity in intangible capital and thus stronger assortative matching.

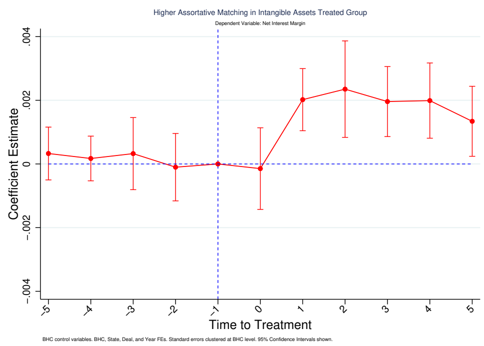
Figures 7a and 7b present results for the higher and lower assortative matching subgroups, respectively, using NIM as the outcome variable. In both panels, we observe stable pre-trends, lending support to the parallel trends assumption. In the post-treatment period, the higher assortative group exhibits a consistent upward trend in NIM, while no significant effects are observed for the lower assortative group. Following the merger, banks with higher assortative matching in intangible capital experienced up to a 0.2 percentage point increase in Net Interest Margin (NIM) compared to banks in the control group. This suggests that banks in better-aligned M&A transactions are more likely to realize pricing or funding advantages that translate into improved interest margins.

Figures 7c and 7d display the dynamic effects on ROL. The higher assortative matching group experiences a statistically significant increase in ROL following the merger, consistent with improved credit allocation or enhanced risk-based pricing enabled by intangible capital alignment. We find that banks involved in mergers with stronger intangible capital matching saw their Return on Loans (ROL) rise by around 0.4 percentage points in the years following the transaction, relative to control group counterparts. In contrast, the lower assortative group shows no comparable pattern.

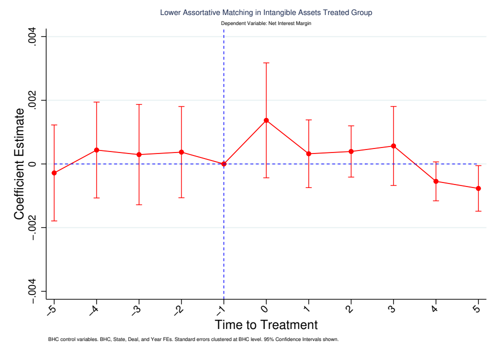
Figures 7e and 7f examine changes in operating efficiency growth. For the higher assortative matching group, we find a sustained upward trend post-merger, with an average annual increase of approximately 6-7 percentage point in operating efficiency growth relative to the control group. These results highlight the role of organizational fit—grounded in intangible capital alignment—in generating operational synergies.

By contrast, the lower assortative matching group exhibits muted and statistically insignificant effects across all outcomes. Taken together, these findings highlight the importance of intangible capital alignment in shaping post-merger performance. Banks with greater similarity in intangible capital are more likely to achieve gains in pricing power, loan profitability, and efficiency—highlighting the strategic value of assortative matching in bank M&A transactions.

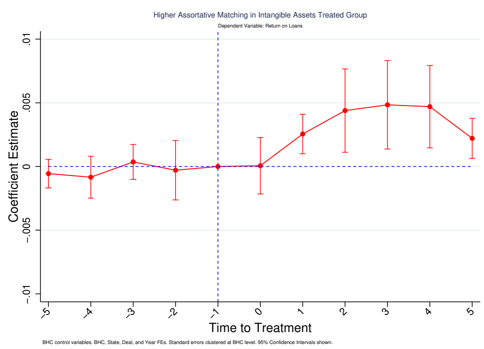
Figure 7: Dynamic DiD Results



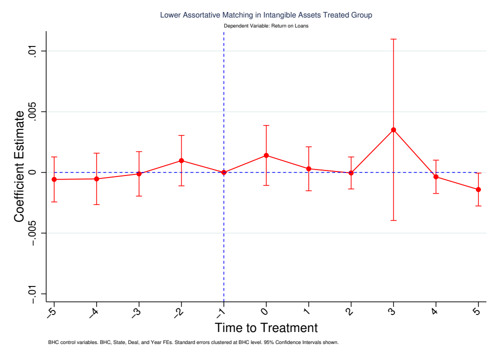

(a) Net Interest Margin - Higher Assortative



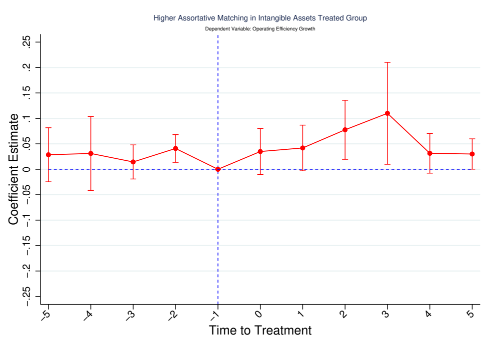

(b) Net Interest Margin - Lower Assortative



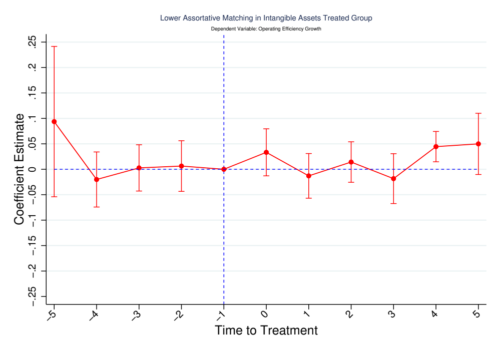

(c) Return on Loans - Higher Assortative




(d) Return on Loans - Lower Assortative




(e) Oper. Eff. Growth - Higher Assortative




(f) Oper. Eff. Growth - Lower Assortative

Note: This figure presents the dynamic difference-in-differences estimates of the regression model outlined in equation (3). We categorize the acquirer banks within the treated group into two categories: acquirer banks with higher and lower assortative matching in terms of intangible capital during one-period before the M&A deal. The regression model includes bank holding company-level control variables (one-period lagged of log total assets, return on equity, total capital-to-asset ratio, loan-to-deposit ratio, and the growth rates of assets, loans, and deposits), as well as year, acquirer bank holding company, acquirer bank holding company state, and deal fixed effects. Standard errors are clustered at the bank holding company level, and confidence intervals are calculated at the 95% level.

# 5 Robustness Checks

We conduct a series of robustness checks to assess whether the observed patterns of assortative matching and performance gains are driven by macroeconomic conditions. Specifically, we examine whether the business cycle systematically affects M&A activity or the degree of matching in bank characteristics. While we find that M&A volumes decline modestly during recessions, this effect disappears once we control for bank-level and regional characteristics. More importantly, we show that the strength of assortative matching—particularly in intangible capital—is not significantly different in recession versus non-recession periods. Both regression analysis and visual evidence confirm that our key findings are not confined to specific episodes of economic expansion or contraction, supporting the view that assortative matching in intangible capital is a persistent feature of bank consolidation. Further details and supporting analyses are provided in Appendix Section D.

# 6 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 strategic 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.

Our key motivations for developing a theoretical model are twofold. First, although our empirical section provides a causal analysis of the relationship between intangible assets, 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. Second, our empirical analysis, by its nature, cannot conduct any counterfactual analyses. We use our theoretical framework to provide counterfactual analyses to see how the degree of merger regulations impacts the likelihood of assortative matching and the change in post-merger efficiency gains to our parameter space.

## 6.1 Setup

There are two markets[6], 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 $\theta$ 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 there 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 $N_{i,j}$. The cost of one unit of intangible assets is also assumed to be \$1 and can be instantaneously adjusted with no friction.[7] 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. Banks with differing utilization rates will invest different amounts of intangible assets in equilibrium. 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

$$m_{i,j}(\cdot) = \phi_{i,j} N_{i,j}$$

where $\phi_{i,j} > 1$. 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 $\alpha > 1$. We allow instantaneous and frictionless adjustment of the intangible asset stock.

Each financial intermediary can also choose to merge.[8] 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

[6]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.

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

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

becomes

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

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 $\psi > 1$.

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 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 $\phi_{A,j}, \phi_{B,j'} > 1$.

### 6.2 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 $\Sigma$ over the next time interval $\Delta$ 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 $\Sigma^{NM}$ state, there is a probability $1 - e^{-\Delta\lambda^{NM}}$ that a positive shock occurs to $\phi_M(\cdot,\cdot)$. The state switches to $\Sigma^{MP}$ 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.

Let $\Pi_{i,j}^{NM}$ represent the present value of a type $j$ bank in market $i$ in the NM state and $\Pi_{i,j}^{MP}$ 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 $\Pi_{i_j,i'_{j'}}^{M}$ represent the expected value of the merger to the type $j$ bank who merges 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 $\Pi_{i,j}^{MP}$, to which at any time the state may return to the NM state with value $\Pi_{i,j}^{NM}$.

### 6.3 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 $\Delta$ 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

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

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 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 $\theta_m$ 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.

For a $\Delta$ 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 $\Delta$ 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 MP 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.

# 7 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 7.1** *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 7.2 provides a sufficient condition to ensure supermodularity of synergies guaranteeing assortative matching.

**Corollary 7.2** *For bank types $j, j'$ where $j \neq j'$ and markets $i$, $i'$ assortative matching will occur if*

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

*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.

### 7.1 Simulations

In our first simulation, we can express equation (4) in Corollary 7.2 as the following ratio:

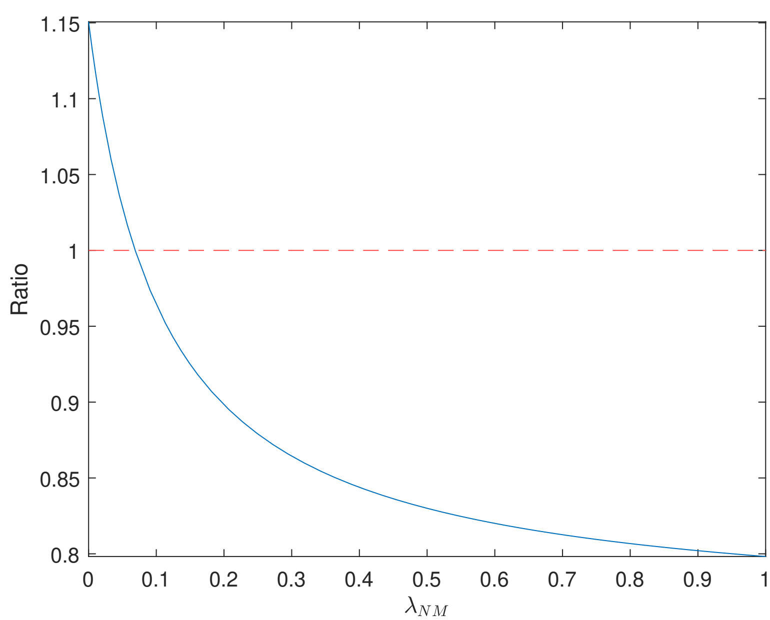
$$\text{Ratio} \equiv \frac{4G[s_{A_l,B_s} - X_{A,l} - X_{B,s}] + q_B(\theta_m)[s_{A_l,B_s} - s_{A_s,B_s}]}{q_A(\theta_m)[s_{A_l,B_l} - s_{A_l,B_s}]}, \tag{5}$$

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, synergy benefits among similar characteristic banks outweigh the associated costs of searching, making assortative matching more favorable. Thus, when the Ratio is less than one, Corollary 7.2 guarantees the assortative matching equilibrium. Conversely, a Ratio above one suggests that the marginal costs of searching may outweigh the synergy benefits, leading to a breakdown of the equilibrium.

To understand why this Ratio matters, we should consider that it captures the regulator's influence on merger patterns. 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 $\lambda^{NM}$ in the NM state. This implies the regulator determines with probability $(1 - e^{-\Delta\lambda^{NM}})$ of banks entering the merger state. Hence, we can uncover the impact of varying regulatory conditions on the likelihood of assortative matching by simulating different values for the state intensity parameter $\lambda^{NM}$.

Table A.6 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 8: Likelihood of Assortative Matching




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

Figure 8 shows how different $\lambda^{NM}$ levels influence the Ratio—and thus the likelihood of meeting the assortative matching condition. We can interpret lower $\lambda^{NM}$ values as being more restrictive policies. When high regulatory barriers inhibit entry into the merger state, banks internalize the costs of re-searching under the merger state due to an initial mismatch. This leads to a potential decline/collapse in assortative matching, as banks that would otherwise form efficient mergers may choose suboptimal mergers to exploit an opportune moment.

Regulators may be concerned with the ex-post efficiency gains (losses) for bank M&As under assortative matching. We conceptualize the efficiency ratio as the monitoring and screening costs divided by revenues given:

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

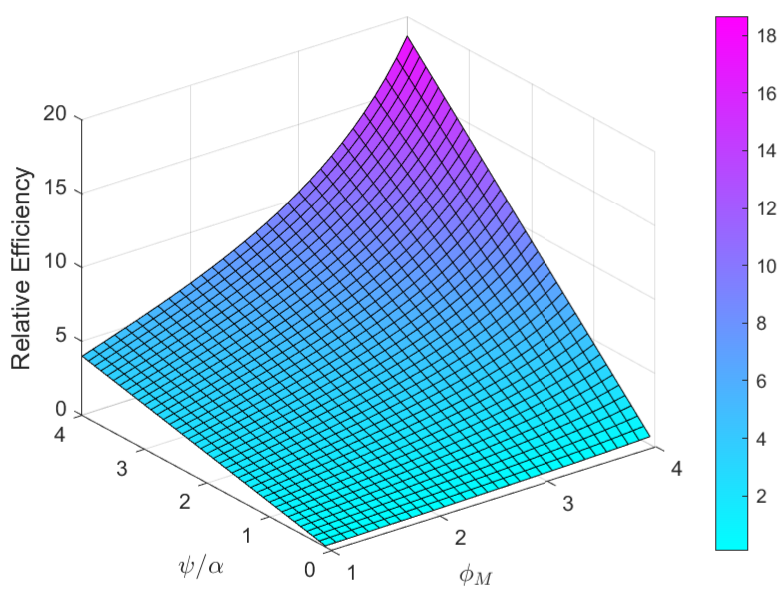
The efficiency ratio serves as a measure of a bank's operational efficiency, with lower ratios indicating a higher degree of efficiency. To compare the efficiency ratios between the standalone and merger cases, we define relative efficiency as the ratio of standalone efficiency to merger efficiency as 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 9 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, $\psi/\alpha$, and (ii) synergy benefits, $\phi_M$.

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. These efficiency losses are partially offset as synergy benefits rise. Conversely, when $\psi/\alpha > 1$, merged banks achieve more significant efficiency gains because a steeper cost function is associated with higher intangible asset stock, resulting in disproportionate marginal revenue gains. Higher synergy benefits amplify these gains, suggesting that when banks have high synergy potential, mergers are likely to improve efficiency in this region with multiples as high as 19.

Figure 9: 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 ($\psi/\alpha$) and synergy benefits ($\phi_M$).

Our model and simulations show how intangible asset accumulation among banks pre- and post-merger can lead to sizable outcome differences. Figure 8 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 9 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.

# 8 Conclusion

This paper sheds new light on the growing importance of intangible capital in shaping the structure and performance of the U.S. banking sector. Against the backdrop of a dramatic decline in the number of commercial banks and a broader economic shift toward knowledge-based production, we investigate how internally generated intangible assets influence merger patterns and outcomes in banking. By developing a novel proxy for intangible capital based on granular noninterest expense data and applying it to U.S. Call Reports, we quantify a previously unobserved but economically salient component of bank capabilities.

Our analysis reveals that intangible capital plays a central role in both the formation and success of bank mergers. We document robust evidence of assortative matching, whereby banks are more likely to merge with partners of similar intangible capital. This matching behavior is not only statistically significant but economically meaningful: only those mergers with higher assortative matching in intangible capital experience improvements in Net Interest Margin, Return on Loans, and Operating Efficiency Growth.

To interpret these findings, we develop a continuous-time search model of bank M&As that incorporates endogenous matching based on intangible capital. The model generates assortative matching equilibria under strategic complementarities and highlights how regulatory frictions can distort the efficiency of matching. Counterfactual simulations reveal that overly restrictive merger approval probabilities can lead to suboptimal matches, while even seemingly well-aligned consolidations may reduce efficiency if they trigger excessive convexity in post-merger monitoring costs. These insights challenge the notion that all mergers among similar banks are necessarily welfare-enhancing and provide a conceptual framework for evaluating regulatory thresholds.

Taken together, our results demonstrate that the intangible capital shapes the dynamics of market structure and consolidation in the financial sector. By integrating new measures, causal identification, and theoretical modeling, this paper offers a comprehensive view of how intangible resources mediate both the process and consequences of financial mergers. Future research could extend these insights by exploring how intangible capital interacts with regulatory goals related to financial stability, and competition.

## 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.

Calomiris, C. W. and D. Nissim (2014). Crisis-related shifts in the market valuation of banking activities. *Journal of Financial Intermediation 23*(3), 400–435.

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.

Eisfeldt, A. L. and D. Papanikolaou (2013). Organization capital and the cross-section of expected returns. *The Journal of Finance 68*(4), 1365–1406.

Ewens, M., R. H. Peters, and S. Wang (2024). Measuring intangible capital with market prices. *Management Science*.

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

Gort, M. (1969). An economic disturbance theory of mergers. *The Quarterly Journal of Economics 83*(4), 624–642.

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.

Modi, K., N. Pierri, Y. Timmer, and M. S. M. Peria (2022). The anatomy of banks' IT investments: Drivers and implications. IMF Working Papers 2022(244), International Monetary Fund.

Nagar, V. and M. V. Rajan (2005). Measuring customer relationships: The case of the retail banking industry. *Management science 51*(6), 904–919.

Nash, R. C. and J. F. Sinkey Jr (1997). On competition, risk, and hidden assets in the market for bank credit cards. *Journal of Banking & Finance 21*(1), 89–112.

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

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.

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 Additional Tables

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

| Variables | Description |
|---|---|
| Operating Efficiency | $\frac{\text{Operating Income}}{\text{Non-interest Expenses}}$ |
| Loan Loss Provision Ratio | $\frac{\text{Loan Loss Provision}}{\text{Total Loans}}$ |
| Capital Adequacy Ratio | $\frac{\text{Total Equity}+\text{Subordinated Debt}}{\text{Total Assets}}$ |
| Return on Assets (ROA) | $\frac{\text{Net Income}}{\text{Total Assets}}$ |
| Return on Equity (ROE) | $\frac{\text{Net Income}}{\text{Total Equity}}$ |
| Return on Loans (ROL) | $\frac{\text{Interest and fees on loans}}{\text{Total Loans}}$ |
| Liquidity Ratio | $\frac{\text{Total Cash + Total Securities}}{\text{Total Assets}}$ |
| Net Interest Margin (NIM) | $\frac{\text{Net Interest Income}}{\text{Total Assets}}$ |
| Total Loans to Deposits | $\frac{\text{Total Loans}}{\text{Total Deposits}}$ |
| Service Charges to Assets | $\frac{\text{Service Charges on Deposits}}{\text{Total Assets}}$ |
| Trading Revenue to Assets | $\frac{\text{Trading Revenue}}{\text{Total Assets}}$ |
| Income from Securities to Assets | $\frac{\text{Interest and Dividend Income on Securities}}{\text{Total Assets}}$ |
| Core Deposits to Assets | $\frac{\text{Demand + Savings + Time Deposits}}{\text{Total Assets}}$ |

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

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

| | Mean | SD | Median | Min | Max | Count |
|---|---|---|---|---|---|---|
| Log Assets | 11.01 | 1.31 | 10.87 | -0.34 | 21.03 | 1736164 |
| Log Deposits | 10.84 | 1.30 | 10.73 | -0.50 | 20.50 | 1735046 |
| Log Loans | 10.38 | 1.43 | 10.26 | -0.65 | 20.07 | 1731394 |
| Log Equity | 8.63 | 1.29 | 8.49 | 0.05 | 18.69 | 1734242 |
| Net Interest Margin | 0.01 | 1.62 | 0.01 | -1.59 | 1826.00 | 1271804 |
| Return on Assets | 0.01 | 6.93 | 0.00 | -50.84 | 8022.00 | 1341810 |
| Return on Equity | 0.02 | 2.25 | 0.03 | -657.80 | 2117.00 | 1341794 |
| Return on Loans | 0.02 | 0.29 | 0.02 | -65.33 | 222.02 | 1337546 |
| Operating Efficiency | 2.69 | 9.97 | 2.49 | -1197.00 | 10397.45 | 1271624 |
| Loan to Deposit Ratio | 2.98 | 260.71 | 0.65 | -0.54 | 116308.00 | 1735046 |
| Service Charges to Assets | 0.00 | 0.01 | 0.00 | -0.48 | 7.00 | 1341808 |
| Trading Revenue to Assets | 0.00 | 0.10 | 0.00 | -0.03 | 71.00 | 494683 |
| Loan Loss Provision Ratio | 0.00 | 0.29 | 0.00 | -85.25 | 301.76 | 1337557 |

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 |
|---|---|---|---|---|---|---|
| Internal Intangible Capital | 3302.944 | 71657.08 | 206.0958 | 0 | 9724738 | 1749325 |
| Goodwill | 12425.3 | 378109.4 | 0 | 0 | 48200000 | 1345944 |
| Other Intangible Assets | 3431.165 | 117438.9 | 0 | 0 | 17200000 | 1216424 |

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

Table A.5: Spreads Between Actual and Hypothetical Mergers

| Variable | Mean Value: Actual Mergers | Mean Value: Hypothetical Mergers | t(diff) | p-value |
|---|---|---|---|---|
| Acq. (Log Assets) - Targ. (Log Assets) | 1.20 | .76 | 8.93 | 0.00 |
| (Acq. (Log Assets) - Targ. (Log Assets))$^2$ | 2.46 | 3.48 | -5.46 | 0.00 |
| Acq. (Log Loans) - Targ. (Log Loans) | 1.32 | .78 | 8.58 | 0.00 |
| \|Acq. (Log Loans) - Targ. (Log Loans)\| | 3.12 | 4.25 | -4.45 | 0.00 |
| Acq. (Log NII) - Targ. (Log NII) | 1.28 | .81 | 9.11 | 0.00 |
| (Acq. (Log NII) - Targ. (Log NII))$^2$ | 2.66 | 3.64 | -5.00 | 0.00 |
| Acq. (Log Intangible Capital) - Targ. (Log Intangible Capital) | .97 | .60 | 7.08 | 0.00 |
| (Acq. (Log Intangible Assets) - Targ. (Log Intangible Assets))$^2$ | 1.93 | 3.44 | -7.70 | 0.00 |

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

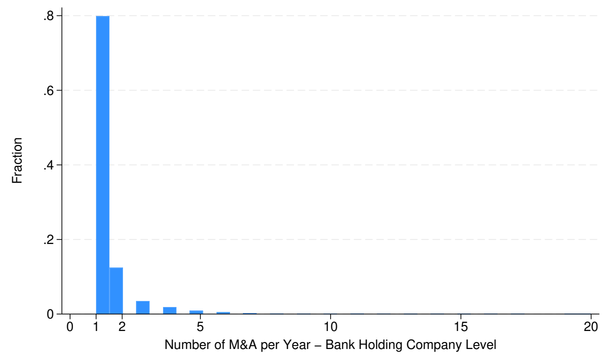
Table A.6: Simulation Parameters

| 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 | $\lambda^{MP}$ | 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 | $\psi, \alpha$ | 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.

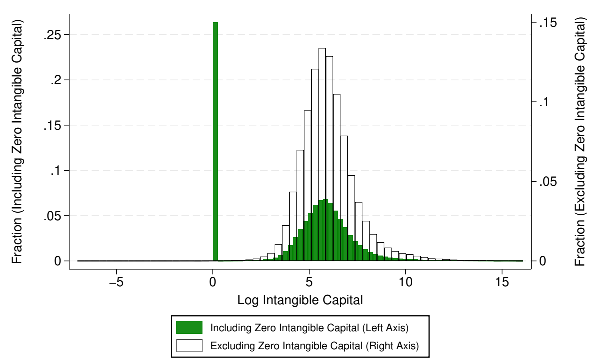
# Appendix B Additional Figures

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



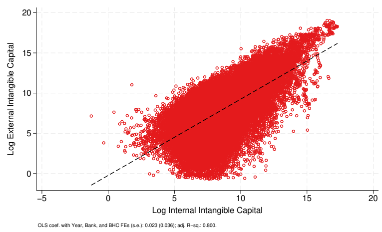

Note: This figure documents the histogram of the number of M&A per year at the bank holding company level.

Figure B.2: Histogram - Log Intangible Capital

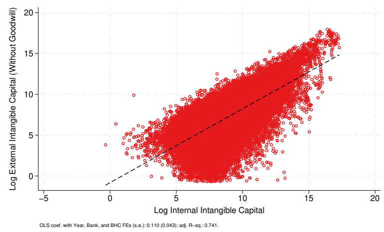



Note: This figure presents the histogram of the logarithm of intangible capital from the quarterly U.S. Call Reports. The left axis displays the histogram of the logarithm of intangible capital, including zero values, while the right axis shows the histogram of the logarithm of non-zero intangible capital.

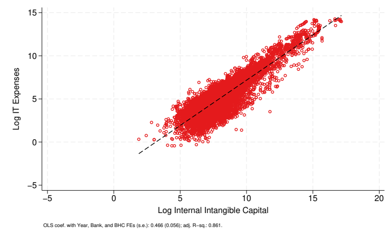
Figure B.3: Intangible-Related Bank Variables and Internal Intangible Capital




(a) External Intangible

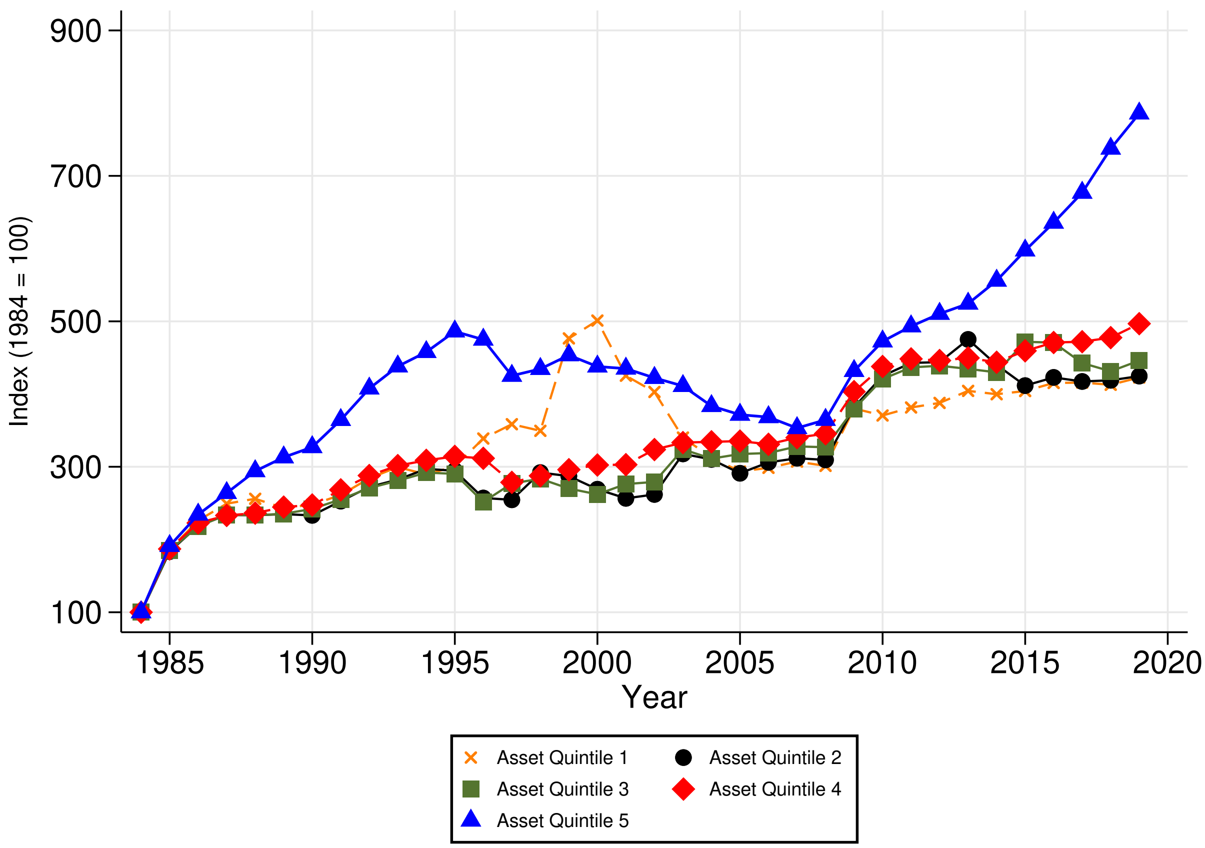



(b) External Intangible (w/o Goodwill)




(c) IT Expense

Figure B.4: Intangible Capital by Asset Quintile




Note: This figure plots the annual mean of index values for total intangible capital by asset quintiles, where quintiles are constructed within each quarter. All index series are normalized to 100 at the beginning of the sample period.

## Appendix C  Measurement of Bank Intangible Capital

As our paper emphasizes the importance of intangible capital in bank M&A activities, we carefully construct intangible capital following financial reporting guidelines. Standard accounting measures often fail to accurately capture intangible capital in the banking sector. Most intangible-related expenditures—such as those associated with software, customer relationships, or organizational development—are expensed rather than capitalized, leading to systematic undermeasurement in balance sheet data. As a result, empirical research that relies on standard financial statements tends to omit these productivity-enhancing investments, obscuring the true extent of banks' capital accumulation and organizational capabilities.

To address this gap, we develop a novel, forward-looking measure of bank intangible capital using granular regulatory filings from the U.S. Call Reports. Our approach leverages detailed information from the *Other Noninterest Expense* category (RIAD4092), which captures a wide range of operational expenditures, many of which are plausibly associated with intangible investment. Unlike externally reported intangibles such as goodwill, our measure captures internally generated and systematically recurring expenditures related to IT, marketing, and organizational development.

We define a flow-based proxy for intangible investment as the sum of selected subcomponents within RIAD4092. Specifically, this includes Data Processing Expenses (RIADC017), Marketing and Other Professional Services (RIAD0497), Telecommunications Expense (RIADF559), and itemized expense lines (RIAD4464–RIAD4468), where the latter are included only if their associated textual descriptions indicate intangible-related content. This selection targets categories most closely linked to intangible investment that is expensed rather than capitalized under prevailing accounting standards. Data processing and telecommunications costs typically reflect investments in software development and digital infrastructure, while marketing expenditures support brand equity and customer analytics. The itemized lines provide further detail on large, heterogeneous expenses; by classifying their textual descriptions using a curated keyword dictionary, we capture additional investments in branding, staff training, and strategic consulting—activities that are central to organizational capital but often invisible in traditional asset accounts.

To identify intangible-relevant entries, we extract and standardize the text fields associated with each itemized expense (TEXT4464, TEXT4467, TEXT4468). We then apply a flexible keyword search procedure to flag terms associated with intangible themes, including software (e.g., "`software`", "`IT`", "`digital banking`"), human capital (e.g., "`training`", "`staff`", "`talent`"), branding (e.g., "`marketing`", "`advertising`", "`reputation`"), and organizational structure (e.g., "`governance`", "`strategy`", "`efficiency`"). Aggregating these sub-items to the bank-quarter level, we find that the average share of identified subcomponents within *Other Noninterest Expense* is approximately 28%. Based on this finding, we assume that 30% of total noninterest expenses reflect intangible investment. This assumption is also consistent with the approach of Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017), which measure organizational capital in non-financial firms as 30% of Selling, General, and Administrative (SG&A) expenses—a cost category conceptually related to *Other Noninterest Expense* in the financial sector. We capitalize this flow measure into a stock using a standard perpetual inventory method:

$$\text{Intangible Capital}_{it} = (1-\delta) \times \text{Intangible Capital}_{i,t-1} + 0.3 \times \text{Other Noninterest Expense}_{it}$$

where $\delta = 0.3$, consistent with estimated depreciation rates in Peters and Taylor (2017) and Ewens et al. (2024). This construction yields a dynamic measure of internally generated intangible capital that captures latent investments in productivity-enhancing capabilities—investments that are central to bank performance but typically omitted from financial statements. Figure B.2 documents the histogram of the logarithm of intangible capital.

To validate our constructed measure of internally generated intangible capital, we compare it against externally reported intangible assets from the Call Reports. The primary item for intangible assets is *Intangible Assets* (RCFD2143 or RCON2143), which includes both goodwill and other identifiable intangibles. We use RCFD2143 (or RCON2143) when directly available. When it is not reported, we reconstruct total intangible assets by aggregating subitems, following changes in regulatory reporting requirements over time. Specifically, we track two broad categories: *Goodwill* (RCFD3163 or RCON3163), which is consistently reported throughout our sample period, and *Other Intangible Assets*, which are reported under various line items depending on the year. Until 2001, *Mortgage Servicing Assets* (RCFD3164 or RCON3164) and *Other Identifiable Intangible Assets* (RCFD3165 or RCON3165) are disclosed as separate components. From the early 1990s to 1998, further disaggregation is available, including *Purchased Credit Card Relationships* (RCFD5506 or RCON5506) and *All Other Identifiable Intangible Assets* (RCFD5507 or RCON5507) as subcomponents of RCFD3165. Starting in 2001, *Other Intangible Assets* (RCFD0426 or RCON0426) is used to consolidate non-goodwill intangibles, including *Mortgage Servicing Assets*, *Purchased Credit Card Relationships and Nonmortgage Servicing Assets* (RCFDB026 or RCONB026), and *All Other Identifiable Intangible Assets* (RCFD5507 or RCON5507). Table A.4 presents the summary statistics of the intangible capital and external intangible assets in the quarterly U.S. Call Reports.

Figures B.3a and B.3b present the yearly association between externally reported intangible assets (with and without goodwill) and our measure of internally generated intangible capital. We find a strong positive correlation, which supports the interpretation that our expense-based measure captures economically meaningful intangible investment activity within banks. We do not include externally reported intangible assets in our primary analysis, as they do not adequately capture banks' internally generated capabilities in areas such as technology, organizational processes, or human capital. Much of the reported intangible asset stock—particularly goodwill—reflects acquisition-related accounting rather than productive investment. For example, Masulis et al. (2023) find that goodwill does not significantly influence acquirer announcement returns and argue it is more likely to reflect managerial incentives or overpayment than future synergies. Thus, including goodwill conflates valuation effects with true intangible capital accumulation. Even other identifiable intangible assets are typically limited to acquired items, such as servicing rights or purchased customer relationships, and may not reflect the breadth of internally developed knowledge, systems, or brand equity. For this reason, we focus on our internally constructed measure of intangible capital derived from expensed investments, which we believe more accurately represents the latent capabilities that drive bank performance.

We further validate our measure by comparing it to the bank-level IT expense measures from Modi et al. (2022). Figure B.3c shows a positive and statistically significant association between their IT expenses and our constructed measure of intangible capital, reinforcing the interpretation that our metric captures banks' underlying intangible capabilities and technology-related investments. While this validation confirms that our measure correlates with technology-related spending, it is important to note that our constructed intangible capital measure is substantially broader in scope. In addition to IT-related expenses, it captures investments in marketing, customer relationships, staff training, strategic consulting, and other organizational development activities that are typically expensed and omitted from capital accounts.

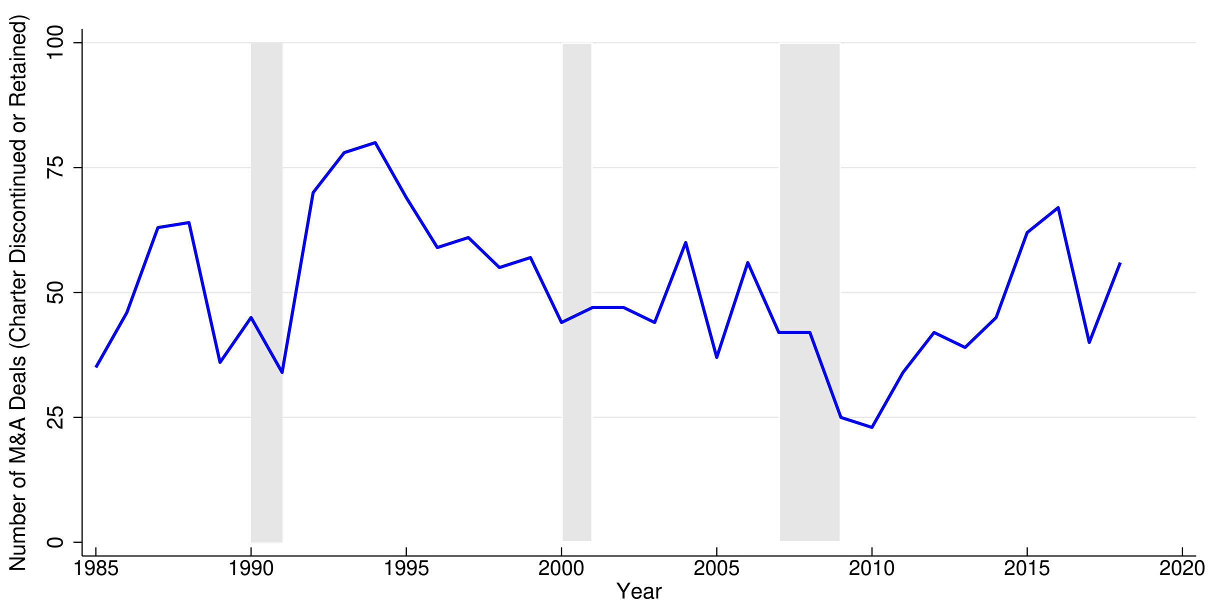
Figure B.4 shows the evolution of intangible capital across banks grouped by asset quintiles. For each quarter, banks are sorted into five quintiles based on their assets, and the annual average intangible capital within each quintile is calculated. These values are then indexed to 100 at the beginning of the sample period. The figure reveals a persistent divergence over time: banks in the highest quintile consistently accumulate intangible capital at a faster rate than smaller banks. This widening gap suggests the disproportionate capacity of large banks to invest in internally generated organizational capital, reinforcing the strategic advantages of scale in the intangible economy.

# Appendix D Robustness Checks

## D.1 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.

Figure D.1: 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.

First of all, Figure D.1 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.

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 D.1 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.

Table D.1: Probit Regression – M&A vs. Recession

| | M&A Indicator | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Recession | -0.0749** | -0.0597* | -0.195 | -0.193 |
| | (0.0265) | (0.0266) | (0.177) | (0.177) |
| Control Variables | No | Yes | Yes | Yes |
| Year FE | No | No | Yes | Yes |
| Acquirer County FE | No | No | No | Yes |
| Observations | 111539 | 111363 | 110902 | 110788 |

Note: This table presents Probit regression estimates where the dependent variable equals 1 if the observation is a bank M&A event, and 0 otherwise. The main explanatory variable is a recession indicator, equal to 1 for years overlapping with NBER recession periods (1975, 1980–1982, 1990–1991, 2001, and 2007–2009). Control variables include the logarithms of total assets, equity, deposits, and loans at the acquirer bank level. Standard errors (in parentheses) are clustered at the acquirer bank's county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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. In other words, how does the sorting mechanism work once banks decide to pursue an M&A transaction? Does the cyclical behavior of the economy impact sorting and assortative matching? To test this question, following our previous insights, we regress our proxy empirical measures of assortative matching (the square of differences of i) logarithm of loans, ii) logarithm of net interest income (NII), and iii) logarithm of intangible capital in merger pairs on a dummy variable for recession periods, controlling for the acquirer-level and target-level logarithms of total assets. Table D.2 indicates that the dummy variable for recession periods is insignificant in explaining the assortative matching measures (except the one for net interest income). 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.

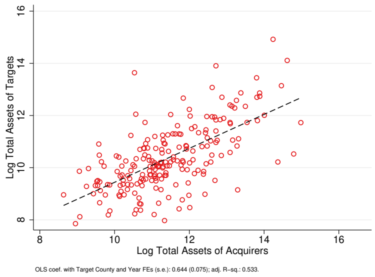
Table D.2: Assortative Matching vs. Recession

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\lvert$Log Loans$\rvert^2$ | $\lvert$Log NII$\rvert^2$ | $\lvert$Log Intangible Capital$\rvert^2$ |
| Recession | 0.274 | 1.176** | 0.127 |
| | (0.567) | (0.399) | (0.735) |
| Control Variables | Yes | Yes | Yes |
| Acquirer Bank FE | Yes | Yes | Yes |
| Target County FE | Yes | Yes | Yes |
| $R^2$ | 0.896 | 0.922 | 0.817 |
| Observation | 499 | 454 | 458 |

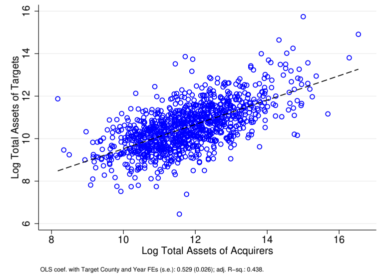
Note: Dependent variables are square of differences of i) logarithm of loans, ii) logarithm of net interest income (NII), and iii) logarithm of intangible capital in merger pairs, which are our proxies of the degree of assortative matching. The main explanatory variable of interest is a dummy variable 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 D.2 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.

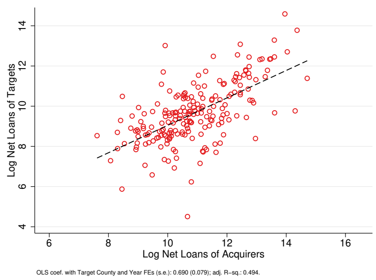
Figure D.2: Assortative Matching - Recession and Other Periods



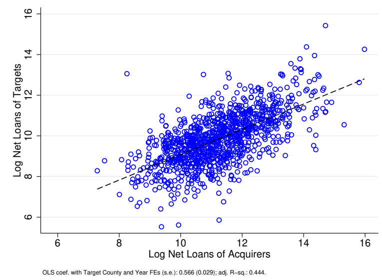

(a) Assets - Recession Per.




(b) Assets - Other Per.

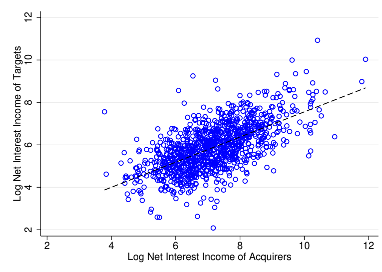



(c) Loans - Recession Per.

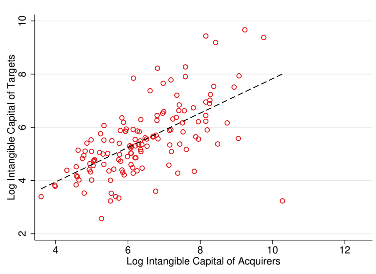



(d) Loans - Other Per.

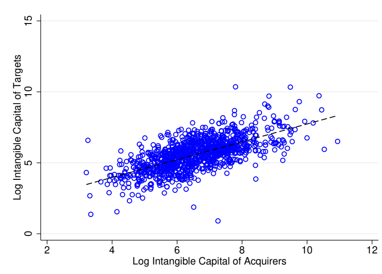

(e) NII - Recession Per.




(f) NII - Other Per.




(g) Intangible Capital - Recession Per.




(h) Intangible Capital - 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 capital, 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.

# Appendix E Derivations

## E.1 Proof of Proposition 7.1

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

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

where

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

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

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

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 $\Pi_{A,j}^{NM}$ we arrive at

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

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

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

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

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

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

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

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. □

### E.2 Proof of Corollary 7.2

We require $\Pi_{i_j,i'_{j'}}^{M} < \Pi_{i,j}^{MP}$ which simplifies to $s_{i_j,i'_{j'}} - \Pi_{i',j'}^{MP} < \Pi_{i,j}^{MP}$. We can make the appropriate substitutions from Proposition 7.1, and the inequality follows. Similarly, when banks of the same type are matched, we also require $\Pi_{i_j,i'_j}^{M} > \Pi_{i,j}^{MP}$ which simplifies to $s_{i_j,i'_j} - \Pi_{i',j}^{MP} > \Pi_{i,j}^{MP}$ which holds as synergy benefits are positive. □