Does Banking Consolidation Harm Households?*

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Keywords: Bank mergers, mortgage rates, approval rates, delinquency rates, market concentration, household finance

JEL classification: G21, G34, R31, G18, O16

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1. Introduction

Bank consolidation has reduced the number of active banks and thrifts by nearly 70 percent (from 14,417 to 4,379 institutions) between 1985 and 2020. Moreover, asset concentration has increased dramatically as well, with the number of banks controlling half of all banking assets falling from 91 to just 10 institutions over this period.[1] This consolidation has intensified regulatory and policymaker concerns that bank mergers erode competition and harm consumers.[2] These concerns are particularly salient for mortgage lending, the primary source (more than two-thirds) of American consumer debt.[3] In this study, we directly examine bank consolidation and mortgage markets, finding mortgage rates, approval rates, and loan performance all remain stable after bank mergers, challenging the view that bank mergers systematically harm households by exercising market power.

Empirically, we identify the merger effect by employing a stacked panel event study difference-in-differences (DiD) design that compares the acquiring and target banks to control institutions within the same local markets before and after the merger. We find that changes in rates, approval rates, and delinquency rates in simple pre-post comparisons reflect portfolio composition effects rather than strategic responses to reduced competition. These composition effects arise naturally. For instance, when a large bank charging low rates acquires a community bank charging higher rates, post-merger rates mechanically rise. Examining rate *distributions* confirms this interpretation: acquiring banks' rate distributions do not change around mergers.

Although measuring the welfare effects of consolidation is difficult in practice, we compile a unique dataset that allows us to jointly observe mortgage pricing, application outcomes,

[1] See: https://banks.data.fdic.gov/explore/historical/ and "How much money do banks in the US control?"

[2] The 2021 Bank Merger Review Modernization Act increases regulatory scrutiny of proposed mergers' competitive effects on specific financial products and in 2022 the FDIC called for comments on the current effectiveness of the 1960 Bank Merger Act.

[3] See https://www.fool.com/the-ascent/research/average-household-debt/

and subsequent loan performance at scale and over time. Our data allows us to distinguish true strategic responses from changes in borrower and bank characteristics. More specifically, we combine banking merger data for nearly 5,000 merger events with confidential borrower data for virtually all (44 million) U.S. mortgages initiated over nearly three decades, ensuring our results hold across diverse market conditions and regulatory regimes. This granularity allows us to examine post-merger prices, approval rates, and loan performance changes that help to separate price responses from changes in screening and distinguish efficiency gains from market power effects.

At a high level, it is perhaps not surprising that we find no evidence of harm despite decades of bank consolidation. Despite extensive consolidation at the national level, the typical county hosts over 130 active lenders in any given quarter. Market shares are highly fragmented—the median lender holds just 0.4 percent—and Herfindahl-Hirschman Index (HHI) levels remain well below the 1,000 threshold used in deposit-market merger review to classify markets as unconcentrated. In fact, competition often intensifies around merger events: when large banks acquire community banks, the number of active lenders in affected counties rises from about 150 to 185 and county-level HHI declines from about 560 to 470–510, patterns inconsistent with strategies to enhance market power.

Our analysis of pre-merger characteristics reveals systematic sorting among merger types that also challenges the market-power story. We find that community banks acquired by large institutions look fundamentally different from those acquired by other community banks: community banks targeted by larger institutions keep 41 percent of their mortgages in portfolio—more than ten times the four percent rate of community–community targets. Moreover, community bank targets of larger institutions are more profitable and more mortgage-intensive (per employee), offer fewer Federal Housing Administration (FHA) mortgages and loans with higher rates than community–community targets. These differences point to distinct merger motives where large banks target small relationship-intensive lenders to access established customer bases while providing scale for securitization and fund-

ing. Community bank acquirers, by contrast, target relatively weaker peers, adding scale rather than opportunities to exercise market power (Buchak et al., 2018; Fuster et al., 2019; Benson et al., 2024b; Jiang, 2023).

Our study contributes to the literature on bank mergers and consumer welfare in three ways. First, we simultaneously examine pricing, credit access, and loan performance with the most comprehensive data to date (44 million mortgages spanning nearly 5,000 merger events over nearly thirty years) coupled with borrower-level characteristics to achieve internal validity that studies focusing on single outcomes cannot. Second, we offer novel evidence on local mortgage markets, documenting lender counts, market shares, and concentration metrics that reflect vigorous competition despite industry consolidation. Although policymakers have intensified scrutiny of bank mergers over market power concerns, our evidence suggests mortgage markets remain strongly competitive. Third, we characterize the premerger attributes of acquiring and target institutions, revealing efficiency-driven selection patterns. Methodologically, our DiD design with bank-county-merger fixed effects isolates bank behaviors from mechanical composition effects, demonstrating that rate changes in simple pre-post comparisons reflect portfolio averaging rather than strategic pricing.

Our results align with studies documenting efficiency gains in mergers (e.g., Sapienza, 2002; Focarelli and Panetta, 2003; Panetta, Schivardi, and Shum, 2009; Erel, 2011; Akkus, Cookson, and Hortaçsu, 2016; Levine, Lin, and Wang, 2020).[4] Relatedly, Kovner, Vickery, and Zhou (2014) document economies of scale in bank operating costs and Minton, Taboada, and Williamson (2024) show that community bank consolidation can boost local investment.[5] Although Huber (2021) shows that larger banks can harm some borrowers in Germany and Garmaise and Moskowitz (2006) link merger activity to tighter credit conditions, we find

[4]Using nationwide market share gains from mergers to proxy for the effects of efficiency gains or cost synergies, Ratnadiwakara and Yerramilli (2022) find no support for efficiency gains.

[5]Buchak and Jørring (2021) show that mortgage lending competition is highly local and Amel, Anenberg, and Jorgensen (2018) discuss the geographic scope of retail mortgage markets. Bird, Du, and Karolyi (2024) show that bank mergers can generate cross-market spillovers—highlighting challenges for geographic market definition.

no adverse effects from U.S. bank mergers. Indeed, Park and Pennacchi (2009) show that mergers can intensify loan competition. Allen, Clark, and Houde (2014) examine Canadian mergers and find price dispersion depends on local market structure—consistent with our finding that mergers in fragmented U.S. markets do not increase rates. Our evidence on business model sorting—large banks targeting portfolio lenders, community banks merging with high-cost peers—echoes Erel, Liao, and Weisbach (2012), who find efficiency motivations dominate merger selection.

Our work also contributes to the literature on consolidation and credit access. Our stable approval rates provide direct micro-level evidence consistent with aggregate patterns found by Jayaratne and Strahan (1996), Strahan and Weston (1998), Black and Strahan (2002) and Beck, Levine, and Levkov (2010). However, our findings contrast with Nguyen (2019), who document that branch closures reduce credit supply—suggesting merger effects differ from physical contraction of bank presence.

Benson, Blattner, Grundl, Kim, and Onishi (2024a) examine how geographic proximity affects antitrust assessments of bank mergers. Our analysis of rates, approval, and delinquency across a comprehensive sample of mergers provides evidence on actual borrower welfare effects beyond concentration measures. Banks may adjust their post-merger strategies differentially across markets. Our county-level analysis captures this heterogeneity by examining outcomes separately within each local market. Our finding of stable approval rates aligns with Berger, Guedhami, Kim, and Li (2022), who show that relationship lending can insulate borrowers from merger disruptions. Lastly, our market structure evidence complements Syverson (2019) and De Loecker, Eeckhout, and Unger (2020), who argue that concentration measures provide an imperfect guide to market power, and Saidi and Streitz (2021), who show that competition and concentration measures need not map one-to-one into competitive outcomes.

2. Data

We use confidential Home Mortgage Disclosure Act (HMDA) data, which reports the universe of mortgage applications and originations from regulated financial institutions.[6] From over 350 million HMDA mortgage records, we extract detailed information on application outcomes, including application, origination and closing dates, as well as loan amounts, and originator identities. We aggregate mortgage origination at the bank-parent company level using Robert Avery's linking file to properly account for corporate structures and mergers.[7]

We merge confidential HMDA data with the McDash mortgage servicing dataset from Black Knight Financial Services, which provides both loan-level contract terms (interest rates, loan-to-value (LTV) ratios, mortgage duration) and dynamic performance information throughout the loan life cycle. McDash covers mortgages originated between 1994 and 2023, with monthly observations tracking each loan from origination through resolution (e.g., refinancing, delinquency, etc.), allowing us to track delinquencies, foreclosures, prepayments, and other performance metrics, including whether a mortgage remains on the originator's balance sheet (portfolio loans), has been securitized, or sold.

After linking confidential HMDA to McDash and filtering out incomplete records, we obtain approximately 62.6 million unique loans with comprehensive information on origination characteristics and subsequent performance.[8] After applying all filters to ensure data quality, our final sample contains approximately 44.3 million unique mortgages from 1994 until 2023.

[6]Banks and credit unions are generally exempt from HMDA reporting based on asset size and loan volume criteria. In 1995, the asset-size exemption threshold was $29 million and has been adjusted annually for inflation (e.g., $42 million in 2013, $50 million in 2022, $58 million in 2025). A closed-end mortgage loan volume threshold was introduced in 2018, initially set at 25 loans in each of the prior two years, raised to 100 loans in 2020, then reverted to 25 loans in 2022.

[7]Avery's method creates consistent institution definitions over time by mapping individual charter identifiers to their parent bank holding companies. HMDA data utilizes multiple identifier systems that evolve, with our earlier sample years using identifiers assigned by regulatory agencies and later years incorporating universal legal entity identifiers. We obtain crosswalk files that map individual bank identifiers to their parent bank holding companies, allowing us to construct consistent consolidated lender identifiers that only change when mergers genuinely change ownership.

[8]We drop observations with missing information on interest rate, applicant income, LTV ratio, FICO score, amount, maturity, rate type, mortgage type, occupancy type, and repayment status.

We collect bank merger information from the Federal Reserve's National Information Center (NIC) database, which provides comprehensive coverage of bank acquisitions and regulatory approvals.[9] The NIC data includes identities of acquiring and target institutions (Research, Statistics, Supervision, Discount (RSSD) identifiers), transaction announcement and completion dates, pre-merger asset sizes for both acquirer and target, and transaction types and regulatory approval status. We identify 4,829 distinct merger events occurring between 1996–2021 (two years after the start and two years before the end of our HMDA/McDash data availability) involving both horizontal mergers (bank-to-bank) and bank acquisitions of non-bank mortgage originators.

[Figure 1 about here]

Figure 1 displays bank mergers over time, averaging 1,080 per year from 1996–2021. After restricting our analysis to mergers between HMDA filers only, our sample includes about 186 bank mergers per year on average (about 17 percent of all mergers).

Within our sample, we classify banks as community banks or large/regional banks by size, based on total assets following thresholds established by the Dodd-Frank Act in 2010 (with inflation adjustments). Community banks have total assets below $10 billion, regional banks have total assets between $10 billion and $100 billion, and large banks have total assets above $100 billion.[10]

For tractability in our empirical analysis, we consolidate large and regional banks into a single category. This grouping reduces computational complexity while maintaining meaningful size distinctions, as both large and regional banks differ substantially from community banks in terms of organizational structure, geographic footprint, and lending operations so

[9]These regulatory filings document all transactions involving insured depository institutions.

[10]We inflation-adjust these thresholds by dividing by the GDP deflator to maintain consistent real size classifications. For robustness, we apply pre-2005 thresholds of $1 billion for community banks and $50 billion for large banks, then adopt $10 billion and $100 billion thresholds after 2005 since using the GDP deflator results in a 1994 community bank threshold of approximately $6 billion. Our results are robust to this alternative.

we contrast between larger, diversified institutions and smaller, locally-focused community banks.[11]

Table 1 presents the distribution of mergers by acquirer and target size. The banking consolidation landscape is dominated by horizontal mergers within size classes, with community–community mergers representing the largest category (2,642 cases, 55 percent of all mergers). Community banks are disproportionately acquisition targets, accounting for 90 percent of all targets (4,325 institutions), highlighting why concerns have been raised about consumer harm. Our final sample comprises 2,642 and 2,187 community and large bank acquirers, respectively. These mergers span 2,683 distinct counties.[12]

[Table 1 about here]

We also obtain bank financial information from the Federal Reserve's merger-adjusted call reports (TINY database), which provide quarterly balance sheet and income statement data adjusted for merger activities. These data provide total assets and liabilities, income statement items including net interest income and non-interest income, loan portfolio composition, and various regulatory measures and capital ratios. The merger-adjusted data are essential for this analysis, as they account for restructuring and asset transfers around bank mergers, allowing us to measure bank characteristics more accurately and more consistently.

Our primary analytical sample is a merger-bank-county-quarter panel designed for stacked event study DiD estimation, tracking mortgage outcomes for acquiring banks, target banks, and control banks across a 17-quarter event window spanning merger completion.[13] We include mortgages by target banks up to two quarters before the merger completion date

[11] Distinguishing between regional and large banks does not substantially change our results.

[12] The scale of this data distinguishes our study from the existing literature, which typically examines substantially smaller merger samples.

[13] We apply several filters to ensure clean identification: we require targets to maintain positive market share in the county during the two years pre-merger; we exclude counties experiencing multiple merger events within our 17-quarter event window, merger-county combinations where acquirers lack pre-merger presence (to avoid confounding market entry with merger effects), and mergers completed during 2007Q1–2009Q4; we ensure control banks remain untreated by excluding any bank experiencing a merger in that county during the 17-quarter window; and we drop non-banks from the control group.

to avoid potential misclassification issues (HMDA data reports some mortgages originated prior to the completion date under the acquirer's identifier while the merger is in progress).

To analyze mortgage market competitiveness, we construct a county-quarter panel dataset aggregating all mortgages at the local market level to calculate market structure measures including lender counts, HHI, and individual lender market shares. For this analysis, we use the universe of loan originations in confidential HMDA, including both bank and non-bank lenders, allowing us to capture the full competitive landscape and address sample-selection biases. This data shows that local mortgage markets remain highly fragmented despite extensive industry consolidation. The typical county features more than 100 different lenders originating mortgages in any given quarter, resulting in HHI levels well below regulatory concentration thresholds.

We also construct bank-county-quarter data tracking each institution's lending activity, market share, portfolio retention rates, and product composition, and bank-year data from merger-adjusted call reports providing balance sheet and income statement information. These data reveal that targets exhibit characteristics suggesting competitive weakness—such as relatively high expense ratios, lower profitability, and, for community banks acquired by large institutions, substantially higher portfolio retention rates.

3. Methodology

Our empirical strategy exploits the geographic and temporal variation in bank merger activity to identify effects on mortgage market outcomes. Banks operate across multiple counties, with large banks having a wide presence, whereas community banks focus on local markets.[14] This geographic dispersion creates significant heterogeneity in acquirer-target overlap across counties during merger events, providing valuable variation in treatment intensity across banks, counties, and time periods. We concentrate our analysis on counties where the target

[14]The median bank in our sample originates mortgages across five counties.

institution had non-zero market share in the eight quarters before the merger, i.e., the markets most likely to experience changes in competitive dynamics. [15]

To examine the impact of mergers on the cost of credit to households, we first construct a residualized interest rate measure that isolates pricing variation unrelated to observable loan risk characteristics and market conditions. We calculate the residual interest rate r^* as follows:

$$r_{i,b,c,t} = \mathrm{X}_{i,b,c,t}\beta + \alpha_{c,t} + r^*_{i,b,c,t} \ , \tag{1}$$

where $r_{i,b,c,t}$ is the raw mortgage rate for loan i issued by bank b in county c at time t; $X_{i,b,c,t}$ includes comprehensive loan characteristics such as applicant income, FICO credit scores (grouped into 5-point bins), LTV ratios (grouped into integer percentage bins), mortgage amount, loan duration and term indicators, fixed rate indicator, home purchase indicator, loan type classifications (FHA, VA, conventional, etc.), and occupancy status (owner-occupied, investment, second home); $\alpha_{c,t}$ are county $\times$ year-quarter fixed effects that absorb all time-varying market-level factors affecting interest rates; and $r^*_{i,b,c,t}$ is the residual rate (in percentage points) after controlling for these factors.[16] By controlling for loan risk and market factors, we isolate the specific effects of the mergers from differences in mortgage attributes. With outcomes expressed at the merger–bank–county–quarter level, we then estimate dynamic treatment effects around merger completion using a stacked event-study DiD.

We examine three primary outcomes around merger events: residualized interest rates (r^*), approval rates, and delinquency rates. Our analysis combines nonparametric event study plots that illustrate the dynamic evolution of these variables around merger completion with parametric DiD specifications that quantify treatment effects.

[15] To isolate merger effects, we exclude county-quarters experiencing multiple mergers within an eight-quarter window. This filter avoids conflating multiple treatment effects but our results are robust to including concurrent mergers. We also exclude merging banks from our control sample in each event window.

[16] For robustness, we compute the spread between the mortgage rate and the Federal Funds rate and obtain qualitatively similar results.

Our parametric approach employs a stacked panel event study DiD design. The regression model is:

$$Y_{e,c,t,b} = \sum_{\tau=-8}^{8} \beta_\tau \cdot \mathbf{1}[t = t^* + \tau] \times \text{Acquirer}_{e,c,b} + \alpha_{b,c,e} + \gamma_{t,e} + \delta_\tau + \epsilon_{e,c,t,b} \ , \tag{2}$$

where $Y_{e,c,t,b}$ is the outcome variable (residual interest rate, approval rate, or delinquency rate) for merger event e, county c, calendar quarter t, and bank b. The coefficients of interest β_τ measure the treatment effect at event-time quarter τ relative to merger completion. The indicator $\mathbf{1}[t = t^* + \tau]$ equals one when being τ quarters from the merger completion date t^*, and the treatment indicator $\text{Acquirer}_{e,c,b}$ equals one for the treated (merged) entity and zero for control banks. In the stacked panel, pre-merger observations for the target bank are assigned to the acquirer's identifier, so that the treated bank–county cell reflects the combined entity throughout the event window. The bank–county–merger fixed effect $\alpha_{b,c,e}$ thus absorbs the level of the pro-forma merged entity, and β_τ captures deviations from this combined baseline rather than shifts in portfolio composition at the merger date. We include calendar quarter-merger fixed effects $\gamma_{t,e}$ that absorb common time trends within each merger event, and event-time fixed effects δ_τ that control for systematic patterns in outcomes relative to merger timing. The error term is denoted by $\epsilon_{e,c,t,b}$.

This stacked event study design offers several advantages. First, it provides an intuitive counterfactual by comparing treated banks to control banks operating in the same markets during the same time periods. Second, it addresses concerns about negative weighting in staggered DiD designs with heterogeneous treatment effects (Goodman-Bacon, 2021; Callaway and SantAnna, 2021). Third, the fixed effects structure ensures that our estimates are identified from within-event variation, and not from aggregate trends or cross-sectional differences between merger events.

If the underlying motive for the merger is to gain market power, the coefficients β_τ for $\tau \in (1, 2, \ldots, 8)$ will be positive and statistically significant—indicating that households

face higher interest rates after the merger.[17] This empirical design follows the framework in Benson, Blattner, Grundl, Kim, and Onishi (2024a) and addresses several challenges to identification. The stacked DiD design draws identification from *within-event* variation, so that each merger serves as its own quasi-experiment. The event-specific fixed effects $\gamma_{t,e}$ ensure that merger-specific demand or cost shocks do not confound estimates across events, and the bank-county-merger fixed effects $\alpha_{b,c,e}$ allow each institution-market pair to have persistent, potentially unobservable differences from other pairs in the same event. By stacking event-specific balanced panels, we eliminate the negative weighting problem that arises when treatment timing and effect heterogeneity interact (De Chaisemartin and D'Haultfœuille, 2020).

Our empirical design rests on important assumptions. The parallel trends assumption still must hold *within* each merger event: outcomes for treated banks must evolve similarly to those for control banks in the counterfactual absence of the merger. Our evidence supports this assumption: we find flat pre-merger coefficients β_τ for $\tau < 0$, indicating acquiring and control bank outcomes move in tandem before treatment. Since we exclude counties experiencing overlapping mergers and control banks involved in concurrent mergers, we avoid contamination from multiple treatments. Lastly, differences in bank size, geographic overlap, and strategic motives, mean that our estimates should be interpreted as average treatment effects across the events in our sample rather than as single uniform causal parameters.

Our approach relies on a transparent counterfactual: for each merger event, we compare the merging banks outcomes to those of all other banks originating mortgages in the same county and quarter. These lenders face the same concurrent local housing and credit conditions, so their behavior provides a natural benchmark for how pricing, approval decisions, and subsequent loan performance would have evolved absent the merger. Although no control group is perfect, our combination of within-county-quarter comparisons and the fixed

[17] Even though the expected effect on interest rates is clear under the market power hypothesis, the predicted direction of β_τ for mortgage approval rates and delinquency rates remains theoretically ambiguous.

effects in (2) delivers an economically intuitive test of whether mergers alter these key lending decisions.

4. Main results

Bank mergers could affect household welfare by changing the price of credit or the availability of credit. We therefore study three outcomes around merger completion: residualized mortgage rates, approval rates, and mortgage repayments. We present both average event-study plots (to visualize dynamics) and quantified results (from stacked event-study DiD specifications with rich fixed effects regressions).

4.1. Bank mergers and mortgage rates

We track residualized rates (r^*, see equation (1)) that control for borrower and loan characteristics as well as market conditions over a 17-quarter window spanning 8 quarters before and 8 quarters after bank mergers. We focus on rates offered by three distinct groups: acquiring banks, target banks, and control banks.

We exploit the richness of our data to analyze mergers at a granular level, distinguishing between large and community banks, recognizing that the competitive effects and motivations for consolidation may differ systematically by bank size. This stratification is important because community banks and large banks often serve different market segments, employ different origination and underwriting technologies, and differ in loan retention/securitization (Kovner et al., 2014; Minton et al., 2024; Jacewitz and Kupiec, 2012).[18]

Figure 2 presents the evolution of average residualized (or abnormal) interest rates around merger events. Each panel corresponds to a different type of merger based on the sizes of the acquiring and target institutions, and each displays three series: acquiring banks (red

[18]We also classify banks into three categories as community, regional, and large, with consistent results to those reported here.

dashed line), target banks (green short-dashed line), and control banks (blue solid line). The vertical line at quarter zero denotes the merger completion date.

[Insert Figure 2 about here]

Panel (a) examines mergers between two community banks, the most common type in our sample. We observe three main patterns within community—community bank mergers. First, acquiring banks offer rates approximately 5 basis points lower than control banks prior to the merger. This difference suggests community bank acquirers price somewhat more competitively, although the difference is economically modest. Second, targeted community banks also offer slightly more competitive pre-merger rates than control banks (the difference averages three basis points). Third, rates across all three groups remain remarkably stable throughout the post-merger period. We find no evidence of divergence between acquirers and control banks, and no indication that merged community banks adjust pricing during the eight post-merger quarters.

Panel (b) presents a more complex picture when large banks acquire community banks. These mergers represent potentially significant shifts in market structure, as a local community bank gives way to a larger institution. During the pre-merger period, large bank acquirers offer slightly lower rates than control banks, mirroring the pattern in panel (a). However, community banks targeted by larger banks offer pre-merger rates that are 20-30 basis points higher than those of both large bank acquirers and control banks. Following these mergers, the average mortgage rate for the merged institution increases modestly, converging toward control bank rates. This modest rate increase reflects the mechanical effect of combining two lending institutions that offer different pre-merger rates and not market power.

Consider, for example, a large bank originating 1,000 mortgages per quarter at an average residualized rate of 0 basis points acquiring a community bank originating 100 mortgages per quarter at +25 basis points. If both institutions maintain their pre-merger pricing strategies,

the post-merger average rate increases mechanically by averaging the two portfolios. Indeed, the observed rate increase in panel (b) could reflect (i) a purely mechanical effect, (ii) that large banks exploit increased market power by raising their own rates, or (iii) that large banks are offering lower rates to target bank customers. We distinguish among these mechanisms with our DiD analysis below.[19]

Panel (c) plots interest rates around mergers when large banks acquire other large banks. These transactions represent economically significant consolidation given the size of the institutions involved in the merger. With the exception of the first two pre-merger quarters, large bank acquirers, targets, and control banks offer similar average pre-merger residualized rates. This similarity aligns with the hypothesis that large banks operate with similar pricing strategies regardless of acquirer or target status. Post-merger rates remain largely stable for all three groups, with a modest decline of approximately 3-4 basis points during the last four post-merger quarters.

The absence of any sustained increase in rates following large bank mergers suggests that these transactions do not systematically lead to the exercise of market power, as measured by changes in average mortgage rates. Still, the graphical evidence from Figure 2 carries important limitations since simple rate pre-/post- comparisons do not control for unobservable time-varying factors that may differentially affect treated and control banks. For example, if acquiring banks systematically enter mergers when facing particularly favorable local market conditions, post-merger rate stability might reflect these improving conditions rather than the absence of market power effects.

We present formal DiD estimates that address these concerns in Figure 3. Each panel displays treatment effect coefficients (β_τ) measuring how acquiring bank residualized rates evolve relative to control banks after accounting for bank-county-merger and time fixed

[19]One additional observation from panel (b) merits attention. Community banks acquired by large banks charge substantially higher rates than control banks operating in the same markets, suggesting that large banks strategically select targets based on distinguishing characteristics. We examine merger selection patterns in Section 6.

effects. This specification explicitly controls for the mechanical averaging problem by comparing changes within the same bank-county pairs over time.

[Insert Figure 3 about here]

Panel (a) of Figure 3 shows the stacked event-study DiD estimates, β_τ, for mergers between community banks. The pre-merger coefficients are small and statistically indistinguishable from zero, supporting the parallel-trends assumption. Post-merger, β_τ remains close to zero and statistically insignificant through eight quarters. These dynamics corroborate the evidence in Figure 2: community-bank consolidations are not associated with systematic changes in mortgage rates. Any pre-merger level differences shown in Figure 2 panel (a) are absorbed by fixed effects, and we find no treatment effect on r^* after the merger.

Panel (b) addresses the identification challenge highlighted in Figure 2 panel (b), where targets priced mortgages substantially above acquirers, creating scope for misleading composition effects in simple averages. In our stacked DiD specification, pre-merger coefficients are largely insignificant—with the exception of quarters -8, -7, and -3—indicating that, conditional on bank-county-merger fixed effects, merged and control banks follow similar pre-trends. Post-merger estimates of β_τ are not statistically significant, indicating no material effect on rates. Overall, we find no significant increase in r^* around bank mergers. These patterns are consistent with integration dynamics and not the exercise of market power.

Panel (c) presents the dynamic effects for mergers between large banks. As in the other cases, pre-merger β_τ estimates do not display systematic trends. Following the merger, point estimates remain clustered near zero with a small, temporary rise in the first two quarters, followed by small negative (and generally insignificant) coefficients later in the window. Taken together with the level patterns in Figure 2, these event study results indicate that large-bank mergers do not result in persistent mortgage rate increases. If anything, longer-horizon estimates suggest modest decreases in post-merger rates.

Across all three merger types, our stacked panel DiD reveals no evidence of persistent, post-merger increases in residualized mortgage rates. The β_τ profiles are centered near zero, pre-trends are flat, and we can rule out economically large effects. These results confirm that the level plots are confounded by acquirer–target composition effects, particularly in large–community bank mergers.[20] The combined evidence indicates that bank mergers do not systematically raise mortgage rates and any short-run changes are transitory and economically small.

Tables 2 and 3 decompose market and borrower attributes by merger type and provide further corroborating evidence. Table 2 shows modest post-merger increases in lender fees, ranging from \$86 to \$183, with the largest adjustment occurring in community–community mergers. These fee adjustments are economically small relative to total loan costs and coincide with changes in interest rate spreads that suggest a partial shift in revenue sources rather than an increase in overall borrowing costs. Interest rate spreads decline in community–community mergers (from 3.42 to 3.13 pp) and remain broadly stable in large–large mergers, though acquirers in large–community mergers show a modest increase (from 3.16 to 3.23 pp). These movements are not statistically significant.

To complement the summary evidence, we also estimate our stacked event-study DiD specification in equation (2) using lender fees as the dependent variable.[21] Across all merger types, the post-merger treatment effect coefficients are small and statistically insignificant. These results confirm that any level changes in fees reflect compositional shifts rather than strategic price increases.

Table 3 indicates that target banks serve distinct borrower segments, as reflected in substantially higher portfolio retention rates (0.41 for community targets acquired by large banks

[20] In the Online Appendix, we examine the pre-merger distributions of residualized mortgage rates for acquirers, targets, and control banks across merger types (see Figure OA.3). The distributions support the interpretation that the level changes in simple pre-post comparisons reflect cross-sectional differences in pricing across banks rather than post-merger changes in acquiring banks' pricing behavior.

[21] Because HMDA only reports lender fees starting in 2018, this analysis covers only mergers occurring in 2019 and 2020 (see Figure OA.2 in the Online Appendix).

versus 0.09 for acquirers) and lower FHA shares (0.11 versus 0.16 for acquirers). These patterns suggest that target institutions are more inclined to retain loans on their balance sheets rather than securitizing them through government programs. The differences are particularly pronounced comparing community–community and large–large mergers, underscoring that any merger effects vary meaningfully with institutional scale and business model alignment.

4.2. Bank mergers and mortgage approval rates

To examine whether and how bank mergers affect mortgage approval rates we employ a similar empirical strategy as in the previous subsection, examining nonparametric event studies coupled with a DiD analysis. Approval rates provide a distinct lens into merger effects compared to pricing: whereas interest rates reflect competitive intensity and cost pass-through, approval decisions capture changes in credit standards and risk appetite.[22] Prior research documents that bank mergers can lead to lower approval rates, particularly for vulnerable borrower groups (Ratnadiwakara and Yerramilli, 2022), making this dimension critical for assessing consumer welfare effects. As with interest rates, we examine approval rates by merger type, recognizing that community banks and large banks may exhibit fundamentally different lending cultures and underwriting approaches.

Figure 4 presents the evolution of average mortgage approval rates around merger events, with each panel corresponding to different acquirer–target combinations. As before, we display three series: acquiring banks (red dashed line), target banks (green short-dashed line), and control banks (blue solid line), with the vertical line at quarter zero marking merger completion.

[Insert Figure 4 about here]

[22] Unlike the interest rate analysis, where we first residualize using county×quarter fixed effects (equation 1), approval and delinquency outcomes enter the stacked DiD directly. The calendar quarter–merger fixed effects $\gamma_{t,e}$ absorb average time movements across all counties within each event but do not account for county-specific demand or credit shocks. This difference arises because the loan-level contract terms needed for residualization are unavailable for denied applications and for pre-origination delinquency predictions.

Panel (a) examines mergers between community banks. Pre-merger approval rates are slightly higher for target community banks (89 percent) than for acquiring and control banks (87 percent), a pattern consistent with either relatively looser underwriting standards or differences in borrower composition. Post-merger approval rates decline modestly to roughly 87 percent, aligning with pre-merger approval rates of the acquirers. Approval rates among control banks remain highly stable throughout. The post-merger convergence toward acquirer approval levels is consistent with the imposition of acquirer underwriting standards on target institutions and pre-/post- differences remain economically small.

Panel (b) presents a more pronounced pattern for large bank acquisitions of community banks. Pre-merger approval rates for control banks are 87 percent, followed by large acquirers (82 percent) and community targets (78 percent). Post-merger approval rates at acquiring banks decline from 82 percent to about 78 percent, converging toward the pre-merger levels of the targets, whereas control banks remain stable. Although this pattern could be consistent with a tightening of lending standards by large banks after acquiring community institutions, it may also reflect changes in borrower composition or portfolio mix rather than shifts in underwriting *per se*. In any case, the difference between pre- and post-merger approval rates remains economically small.

Panel (c) examines mergers between large banks. Control banks display notably higher pre-merger approval rates (86 percent) than both acquirers and targets (76–77 percent). Post-merger changes are limited, with approval rates at acquiring banks remaining close to 75 percent. Taken together, Figure 4 provides little evidence of economically meaningful changes in approval behavior following bank mergers.

Of course, raw level comparisons may conflate merger effects with compositional or market-wide changes. To isolate any causal impact, Figure 5 presents formal DiD estimates that control for bank-county-merger fixed effects and time-varying shocks. Each panel displays treatment effect coefficients (β_τ) measuring how acquiring bank approval rates evolve relative to control banks after accounting for compositional effects.

[Insert Figure 5 about here]

Panel (a) shows that for community bank mergers, our DiD estimates remain close to zero throughout the post-merger period, with tight confidence intervals that include zero at all horizons. This pattern is consistent with the interest rate evidence reported in Figure 3, Panel (a). Overall, these estimates indicate community bank mergers do not produce statistically significant changes in approval rates.

Panel (b) displays DiD estimates for large banks acquiring community banks, with post-merger point estimates trending slightly negative but mainly statistically insignificant. These results show that the decline in approval rates visible in our levels analysis results from factors other than merger-induced policy changes such as time-varying local economic conditions or an evolution in acquirer lending behavior that would have occurred absent the merger. Panel (c) examines large-large mergers and also reveals insignificant point estimates.

Taken together, our results suggest that bank mergers generate no significant systematic changes in approval rates once we properly account for compositional factors and time-varying heterogeneity across markets. Table 2 provides further confirmation: pre- and post-merger approval rates for acquirers and control banks differ very little across all merger types. Collectively, these patterns reinforce the conclusion that bank mergers do not systematically affect households' access to mortgage financing.

4.3. Bank mergers and mortgage performance

We examine how bank mergers affect the quality of newly-originated mortgages by analyzing subsequent delinquency rates.[23] Although interest rates and approval decisions reflect lending terms at origination, delinquency rates capture ex-post loan performance, providing insight into whether mergers alter risk-taking behavior or underwriting quality. Figure 6 displays average delinquency rates for newly originated mortgages around merger events. Each

[23]We define delinquency as mortgages that become 90+ days delinquent or experience foreclosure, bankruptcy, or similar adverse outcomes at any point through the mortgage's life.

panel shows the three comparison groups: acquiring banks (red dashed), target banks (green short-dashed), and control banks (blue solid), with quarter zero marking merger completion.

[Insert Figure 6 about here]

Panel (a) examines community bank mergers and reveals relatively stable delinquency patterns across all groups throughout our event window. All three groups maintain delinquency rates of approximately 7 percent, with only modest quarter-to-quarter fluctuations. These co-movements suggest that the variations reflect broader market conditions rather than merger-specific effects. Moreover, post-merger delinquency rates for acquirer and control banks remain closely aligned. The stability across groups is consistent with our earlier findings that community bank mergers produce limited changes in pricing or credit standards.

Panel (b) presents a more intriguing pattern for large bank acquisitions of community banks. Large bank acquirers and control banks both maintain delinquency rates of approximately 6 percent throughout the event window, consistent with the averages reported in Table 2.

Panel (c) displays mergers between large banks and shows considerable volatility throughout the event window, reflecting the small sample size. Table 2 indicates a modest increase in acquirer delinquency from 7 to 8 percent on average (though insignificant in our formal tests below).

As above, raw level comparisons may reflect time-varying market conditions rather than merger-induced changes. Figure 7 presents formal DiD delinquency estimates that control for bank-county-merger fixed effects and time-varying factors. Each panel displays treatment effect coefficients (β_τ) measuring changes in acquiring bank delinquency rates relative to control banks. Panel (a) examines community bank mergers. Pre-merger coefficients remain centered near zero, supporting the parallel trends assumption. Post-merger estimates are

similarly close to zero and statistically insignificant across all horizons, indicating no causal effect of community bank mergers on mortgage delinquency.

[Insert Figure 7 about here]

Panel (b) addresses large bank acquisitions of community banks. Despite the apparent pre-merger dynamics in levels shown in Figure 6, our DiD coefficients are small and statistically insignificant across all post-merger quarters. Lastly, Panel (c) examines mergers between large banks and also reveals statistically insignificant point estimates throughout the post-merger window. None of the post-merger coefficients are statistically significant, and we find no evidence of systematic post-merger drift in delinquency rates across merger types. Taken together, the evidence on delinquency reinforces our earlier findings regarding interest rates and approval rates: bank mergers do not systematically alter mortgage market outcomes.

5. How competitive are local mortgage markets?

Understanding the competitive structure of local mortgage markets is important for assessing the effects of bank mergers on household borrowing conditions. In more concentrated markets, consolidation is more likely to translate into increased pricing power, whereas in markets with many active lenders, the effects of individual mergers should be attenuated. In this section, we document that county-level mortgage markets are considerably less concentrated than commonly perceived.

Indeed, policy discussions surrounding bank mergers often presume that local mortgage markets are concentrated, with a handful of dominant lenders controlling credit access. Our analysis is, to our knowledge, the most comprehensive on mortgage market competition around bank mergers and challenges this view by revealing that local mortgage markets exhibit remarkably competitive intensity.[24]

[24]We analyze banks at the parent company level, ensuring that our lender counts reflect true independent competitors and do not artificially inflate competition by treating subsidiaries as separate entities.

[Figure 8 about here]

Figure 8 presents the distribution of lender counts and market concentration across county-quarters in our sample. Panel (a) documents an extraordinary degree of competitive intensity: the typical county-quarter hosts dozens of active mortgage lenders, with the distribution exhibiting substantial right skew. Although a small number of rural counties operate with fewer than 20 lenders (3.5%), the average bank-county-quarter observation involves 164 (median 132) competing lenders—reflecting the competitive environment facing a typical mortgage origination (the unweighted county-quarter mean is 75, median 50; see Table OA.3 in the Online Appendix).[25] These figures dramatically exceed the levels typically assumed in discussions of banking competition and indicate that individual bank mergers occur against a backdrop of intense competition from numerous mortgage providers.

Panel (b) reports the HHI, the standard measure of market concentration used in antitrust analysis. The distribution of HHI values indicates that local mortgage markets are overwhelmingly unconcentrated by regulatory standards. The median HHI across bank-county-quarter observations is approximately 400, well below the 1,000 threshold that the U.S. Department of Justice and Federal Trade Commission use in deposit-market merger review to classify markets as unconcentrated.[26] The 75th percentile remains below 1,000, and only a small fraction of county-quarters exceed the 1,800 threshold for highly concentrated markets—primarily rural areas with limited lending activity.[27] Consistent with these patterns, the vast majority of U.S. mortgage originations occur in markets that are highly competitive by antitrust standards.

[25]Table 4, Panel A, contains summary statistics for number of lenders by county-bank-quarter; Table OA.3 in the Online Appendix reports county-quarter level statistics. These counts include both bank and non-bank lenders, reflecting the full competitive landscape. Because Panel A is at the bank-county-quarter level, these statistics are implicitly weighted toward counties where more banks are active, and are therefore more representative of the competitive environment facing the average mortgage origination. The unweighted county-quarter level statistics (mean of 75 lenders, median of 50) are reported in Table OA.3 in the Online Appendix and are more representative of the average county.

[26]The unweighted county-quarter median HHI is 745 (see Table OA.3 in the Online Appendix). See https://www.justice.gov/atr/herfindahl-hirschman-index.

[27]For details, see Table 4.

[Figure 9 about here]

The highly competitive nature of local mortgage markets is also evident in the geographic distribution of lenders. Figure 9 provides a geographic map of the average number of active lenders across U.S. counties during our sample period. The map reveals substantial spatial heterogeneity: major metropolitan areas along the coasts and the industrial Midwest exhibit the darkest shading, indicating 150-200+ active lenders, whereas rural counties in the Great Plains and Mountain West show lighter shading with 25-75 lenders. Importantly, even the least competitive counties maintain dozens of active lenders.

Table 4, Panel A, provides granular detail on the distribution of lender market shares. The median lender captures only 0.39 percent of its county market, whereas the mean is 1.53 percent. This extreme right skew indicates that the typical lender is a marginal player in any given local market. Even at the 90th percentile, lenders control only 3.6 percent of their county markets. Banks maintain slightly higher market shares than the broader lender population at every percentile, reflecting competitive advantages from branch networks, deposit relationships, and regulatory scale economies but these differences are modest—and non-bank mortgage companies provide substantial competitive discipline.

Table 4, Panel B, documents the geographic scope of bank lending operations, revealing that most banks remain predominantly local institutions despite decades of consolidation in the sector. The median bank originates mortgages in only 5 counties per year-quarter, indicating highly localized operations concentrated around branch networks and established customer bases. The mean of 29 counties reflects substantial right skew driven by a small number of national institutions operating across hundreds of counties. At the 10th percentile, banks operate in just a single county, representing truly community-focused institutions, and even at the 90th percentile, banks originate in only 35 (about 1 percent) of U.S. counties.

This competitive landscape provides crucial context for interpreting our merger effect estimates: in markets with 100+ active competitors (and highly-competitive HHI levels),

individual bank mergers are unlikely to generate substantial market power. We next examine whether merger activity materially changes local market structure itself.

[Figure 10 about here]

Figure 10 presents event-study evidence on market structure changes around mergers (average number of lenders per county-quarter). The patterns reveal a surprising result: rather than increasing concentration, bank mergers are associated with increasing lender counts and declining mortgage concentration (HHI). For Large-Community mergers, the number of active lenders increases by 23 percent from approximately 150 pre-merger (quarter -8) to 185 by quarter +8, and HHI declines by 9–16 percent from 560 to 470-510. Large-Large mergers show a larger 30 percent increase in lender counts and a 20–26 percent decline in concentration. Declines in HHI are observed even though the merger mechanically increases concentration by combining two institutions. The offsetting entry of other competitors dominates the direct consolidation effect since mergers occur disproportionately in expanding markets with positive net entry—see Berger et al. (1999); Hauswald and Marquez (2006); Dimopoulos and Sacchetto (2017); Corbae and D'Erasmo (2021). The strong competition we document appears to discipline pricing behavior and prevents banks from exploiting potential market power following mergers.

Our combined evidence tells a coherent story: bank mergers occur in highly competitive markets where merged institutions face substantial discipline from numerous existing and entering lenders. The local mortgage market structure we document helps explain why consolidation does not translate into materially higher mortgage prices, lower approval rates, or worse loan performance for households.

6. Selection in bank mergers

The patterns documented above raise fundamental questions about why banks merge and which institutions select into mergers. Merger selection can help to interpret our findings, since characteristics of merging banks shape both the competitive effects of consolidation and the welfare implications for borrowers. If mergers involve financially distressed institutions seeking survival, the observed pricing and credit supply patterns may reflect efficiency gains and market discipline rather than the exercise of market power. Conversely, if strong institutions acquire profitable targets to consolidate market power, concerns about reduced competition become more salient.

[Table 5 about here]

Table 5 presents comprehensive financial ratios for both target and acquirer banks, organized by our three merger types. The difference columns—(1)−(2), (2)−(3), and (1)−(3)—report pairwise differences in means across merger types, showing that several of the economically important gaps are statistically significant. The target-side comparisons reveal pronounced heterogeneity. Target banks in community–community mergers are weak and operationally inefficient, with near-zero profitability (return on assets (ROA) of 0.001) and very high expense ratios (non-interest expenses account for 90 percent of total income). By contrast, community banks acquired by large institutions are significantly more profitable (ROA of 0.007), materially more efficient on both expense-ratio measures, and more productive per employee. These targets exhibit higher personnel-expense shares, consistent with more labor-intensive and relationship-focused lending models. These patterns suggest large banks select a distinct subset of healthier but operationally different community lenders.

The acquirer panel also points to systematic scale differences rather than distressed acquirers seeking rescue. Large-bank acquirers have slightly higher profitability, lower non-interest expense ratios, lower deposit reliance, lower data-expense shares, and substantially higher in-

come per employee than community-bank acquirers. These patterns are consistent with large institutions bringing scale, funding capacity, and operational infrastructure to the merger. Operationally, community banks acquired by large institutions show substantially higher personnel expense ratios (over 36 percent of total expenses) relative to community–community targets (25.1 percent), suggesting these banks maintain more labor-intensive, relationship-focused operations. Differences in efficiency ratios between targets and acquirers further underscore potential cost rationalization motives. In community–community mergers, targets operate with non-interest expense to income ratios of 89.8 percent compared to 71.2 percent for acquirers, and total expense to income ratios of 95.2 percent compared to 75.9 percent. These disparities suggest scope for post-merger cost reductions.

Although acquirer profitability lies in a narrow range (ROA between 0.003 and 0.004), the broader acquirer characteristics indicate that acquirer weaknesses do not drive mergers.

The evidence in Table 5 collectively points toward merger selection driven by competitive pressure and efficiency considerations rather than market power motivations. These findings indicate that consolidation concentrates in markets where acquirers already maintain presence rather than entering new territory. Community banks increasingly face competition from larger institutions with superior technology, funding advantages, and operational scale. Mergers provide a mechanism for community banks to survive in an evolving competitive landscape. Large banks selectively acquire community banks whose relationship-based lending models and local market presence complement the acquirer's scale and infrastructure, creating potential synergies. This selection pattern comports with our main empirical findings that mergers result in stable mortgage rates and limited changes in credit supply—as efficiency gains are partially passed through to borrowers in competitive markets.

7. Conclusion

This study examines nearly 5,000 bank mergers over nearly three decades using confidential micro-level data linking mortgage applications to loan performance, providing the most comprehensive analysis of bank consolidation effects on household borrowing to date. We document that mortgage markets remain remarkably competitive despite extensive consolidation, with the typical county featuring over 130 active lenders and concentration levels well below regulatory thresholds. Our main finding is straightforward: bank mergers do not systematically raise mortgage rates or restrict credit access once we properly account for the mechanical averaging that occurs when institutions with different lending characteristics merge. When large banks acquire community banks that charge higher rates, the combined entity's rates rise mechanicallybut this reflects portfolio composition, not predatory pricing. Acquiring banks maintain pre-merger pricing strategies rather than exploiting reduced competition. Efficiency motivates mergers: weaker and less efficient community targets tend to merge with other community banks, whereas large acquirers systematically select more profitable, relationship-intensive community lenders that they can integrate into more efficient originate-to-distribute models.

Our findings speak to fundamental questions about market structure, competition, and the appropriate scope of regulatory intervention in financial markets. Recently, policymakers have initiated legislative proposals and intensified scrutiny of bank mergers, concerned that consolidation harms consumers through increased market power. Our evidence suggests these concerns may be overstated in mortgage markets, where low barriers to entry, product differentiation, and the rise of non-bank lenders maintain competitive discipline even as banks consolidate. As banking continues to evolve with technological change and the growth of fintech competitors, understanding how traditional bank consolidation affects consumers becomes increasingly important for designing regulatory frameworks that balance stability, efficiency, and competition objectives.

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Variable definitions appendix

Variable	Description
Mortgage Characteristics	
Current interest rate	The mortgage interest rate.
Interest rate spread	The difference between the mortgage interest rate and a benchmark rate (e.g., Federal Funds rate).
Interest rate (res.) / r^*	The residual mortgage interest rate after controlling for loan characteristics (applicant income, FICO score, LTV ratio, mortgage amount, duration, rate type, loan purpose, loan type, and occupancy status) and county-quarter fixed effects.
Loan amount	The total mortgage amount.
Loan term / Duration	The duration, in months, of the mortgage.
30-year term	Indicator that equals one if the mortgage has a 30-year (360-month) term.
LTV ratio	The loan-to-value ratio of the mortgage in relation to the home's appraised value.
DTI ratio	The debt-to-income ratio, measuring the borrower's total monthly debt payments relative to monthly gross income.
Fixed rate loan	Indicator that equals one if the mortgage interest rate is fixed for the life of the loan.
Conventional loan	Indicator that equals one if the mortgage is not insured or guaranteed by government agencies (FHA, VA, or USDA).
FHA loan	Indicator that equals one if the mortgage is insured by the Federal Housing Administration, designed for lower-income borrowers with lower down payment requirements.
VA loan	Indicator that equals one if the mortgage is guaranteed by the U.S. Department of Veterans Affairs for eligible veterans and service members.
Home purchase loan	Indicator that equals one if the mortgage purpose is for the purchase of a home (as opposed to refinancing).
Owner-occupied	Indicator that equals one if the mortgagor uses the property as their primary residence.
Portfolio	Indicator that equals one if the lender keeps the mortgage in its own investment portfolio instead of selling it on the secondary market.
Borrower Characteristics	
Applicant income	The annual gross income (in thousands of dollars) of the individual(s) applying for the mortgage.
Original FICO score	The borrower's FICO credit score at the time of mortgage application, ranging from 300 to 850, with higher scores indicating better creditworthiness.
Mortgage Costs and Fees	
Lender fees	Fees charged by the lender for processing and underwriting the mortgage, excluding third-party costs.
Origination charges	Total charges by the lender for originating the mortgage, including application fees, underwriting fees, and processing fees.

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Variable	Description
Discount points	Upfront fees paid to the lender at closing to reduce the mortgage interest rate, where one point equals 1% of the loan amount.
Lender credits	Credits provided by the lender to offset closing costs, often in exchange for a higher interest rate.
Total loan costs	The total of all borrower-paid costs associated with obtaining the mortgage, including origination charges, discount points, and other fees.
Application and Approval Metrics	
Approval rate	The fraction of mortgage applications that are approved by the lender.
Approved loans	The number of mortgage applications approved by a lender in a given county and quarter.
# of applications	The total number of mortgage applications received by a lender in a given county and quarter.
Mortgage Performance	
Delinquency >90 days	Indicator that equals one if the mortgagor's mortgage payments at any point in the sample period are more than 90 days overdue or the mortgage enters foreclosure, bankruptcy, or a similar adverse status.
Delinquent mortgages / Total mortgages	The ratio of mortgages that become 90+ days delinquent or enter foreclosure, bankruptcy, or a similar adverse status to the total number of mortgages in the bank's portfolio.
Market Structure Variables	
HHI (county-quarter)	The Herfindahl-Hirschman Index, calculated as the sum of squared market shares (decimal format, × 10,000) of all lenders in a county-quarter, measuring market concentration. Higher values indicate greater concentration.
# of banks (county-quarter)	The total number of distinct bank lenders (at the parent company level) originating mortgages in a given county and quarter.
Bank market share	The fraction of mortgages originated by a specific bank in a given county and quarter relative to all mortgages originated in that county-quarter.
Bank ranking (market share)	The rank of a bank based on its market share in a given county and quarter, with lower numbers indicating higher market share.
Top-3 share (%)	The combined market share (in percent) of the three largest mortgage lenders in a county-quarter, calculated by summing the individual market shares of the three highest-ranked lenders.
Top-5 share (%)	The combined market share (in percent) of the five largest mortgage lenders in a county-quarter, calculated by summing the individual market shares of the five highest-ranked lenders.
Top-10 share (%)	The combined market share (in percent) of the ten largest mortgage lenders in a county-quarter, calculated by summing the individual market shares of the ten highest-ranked lenders.
Nonbank share (%)	The combined market share (in percent) of all non-bank mortgage lenders (institutions without an RSSD identifier) in a county-quarter.
Number of lenders	The total number of distinct lenders (banks and non-banks, at the parent company level) originating at least one mortgage in a county-quarter.

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Variable	Description
Lenders with ≥1% share	The number of distinct lenders holding at least 1 percent of the mortgage origination market share in a county-quarter.
Lenders with ≥5% share	The number of distinct lenders holding at least 5 percent of the mortgage origination market share in a county-quarter.
Quarterly entry rate (%)	The percentage of lenders in a county-quarter that are entering the local market for the first time, calculated as the number of new entrants divided by the total number of active lenders. A lender is classified as an entrant in the first quarter it appears in a given county.
Quarterly exit rate (%)	The percentage of lenders in a county-quarter that are exiting the local market, calculated as the number of exiting lenders divided by the total number of active lenders. A lender is classified as exiting in its final quarter of activity in a given county.
Top lender persistence (%)	An indicator (expressed in percent) for whether the top-ranked lender by market share in a county retains its rank-one position from the previous quarter. Equals 100 if the same lender holds the top position in consecutive quarters and 0 otherwise.
# of distinct markets as active lender	The number of distinct counties in which a lender originated at least one mortgage in a given year-quarter, measuring the geographic scope of the lender's operations.
Bank Classifications	
Community bank	A bank with total assets below $10 billion (adjusted for inflation using the GDP deflator, with lower thresholds before 2005).
Regional bank	A bank with total assets between $10 billion and $100 billion (adjusted for inflation using the GDP deflator).
Large bank	A bank with total assets above $100 billion (adjusted for inflation using the GDP deflator).
Time Periods	
Pre-M (pre-merger)	The period before a bank merger is completed, typically measured in quarters prior to the merger completion date.
Post-M (post-merger)	The period after a bank merger is completed, typically measured in quarters following the merger completion date.
Bank Financial Ratios	
Mortgages / Total assets	The ratio of total mortgage holdings to total bank assets, indicating the concentration of the bank's portfolio in mortgage lending.
ROA: Net income / Total assets	Return on Assets, calculated as net income divided by total assets, measuring overall bank profitability.
Net interest income / Total assets	Net interest income (interest income minus interest expense) divided by total assets, measuring net interest margin relative to asset size.
Non interest expense / Total income	Non-interest operating expenses divided by total income, measuring operational efficiency.
Total expense / Total income	Total expenses (interest and non-interest) divided by total income, measuring the overall cost-to-income ratio.
Total income / # of employees	Total bank income divided by the number of employees, measuring employee productivity in terms of revenue generation.
Mortgages / # of employees	Total mortgage holdings divided by the number of employees, measuring mortgage lending capacity per employee.

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Variable	**Description**
Personnel expenses / Total expenses	Personnel-related expenses divided by total expenses, indicating the labor intensity of bank operations.
Personnel expenses / Total income	Personnel-related expenses divided by total income, measuring labor costs relative to revenue.
Interest expense / Total liabilities	Interest expenses divided by total liabilities, measuring the average cost of funding.
Interest expense / Total deposits	Interest expenses divided by total deposits, measuring the average interest rate paid on deposits.
Deposits / Total assets	Total deposits divided by total assets, measuring the bank's reliance on deposit funding.
Deposits / Total mortgages	Total deposits divided by total mortgage holdings, indicating the extent to which deposits fund mortgage lending.
Total debt / Total assets	Total debt divided by total assets, measuring the bank's leverage ratio.
Total data expenses / Total income	Technology and data processing expenses divided by total income, measuring the bank's investment in technology infrastructure.

Figure 1: Number of bank mergers by year.

This figure illustrates the number of bank mergers by year from 1996-2021. The bars represent the number of bank mergers in our sample (left axis) involving banks that have filed HMDA reports. The solid line shows the total number of bank mergers (right axis). The percentages above each bar indicate the proportion of all mergers involving two HMDA filers that are included in our sample of bank mergers for each year. Source: NIC.

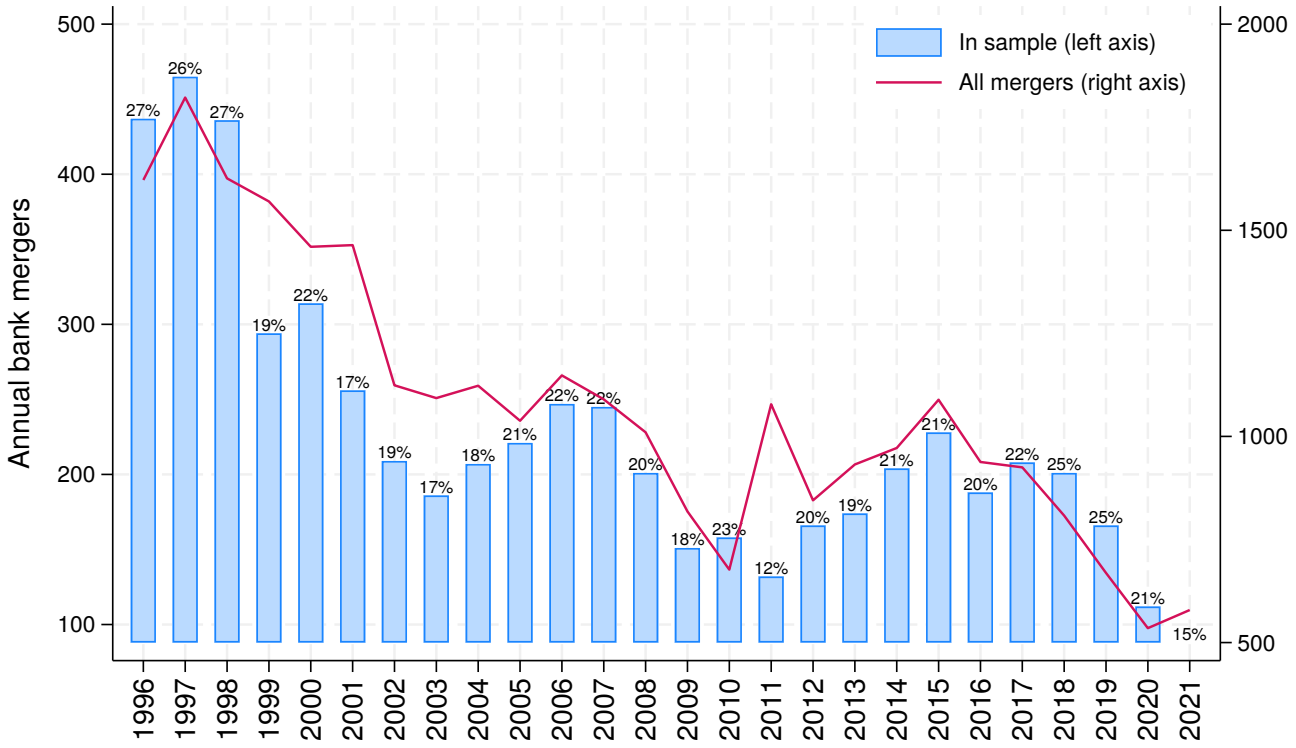


Figure 2: Average abnormal interest rates (r^*)

This figure plots the evolution of average residualized interest rates around merger events for acquiring banks (red dashed), target banks (green short-dashed), and control banks (blue solid). Each panel corresponds to a different merger type based on acquirer and target bank sizes. The vertical line at quarter zero denotes merger completion. Abnormal interest rates (r^*) are the residual mortgage interest rate (in percentage points) after controlling for loan characteristics and county-quarter fixed effects, estimated using regression (1).

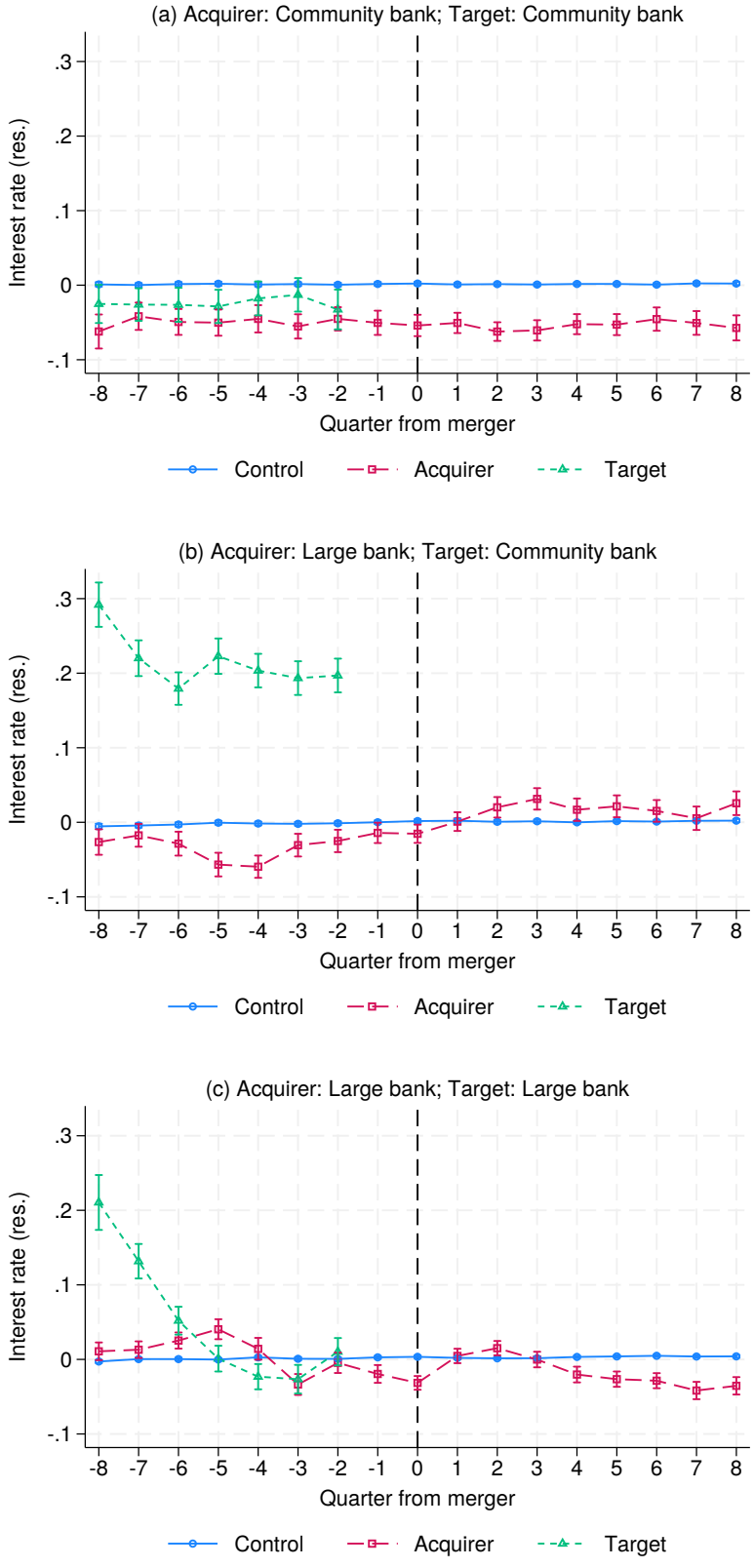


Figure 3: Stacked panel DiD – interest rates

This figure presents DiD estimates of merger effects on residualized interest rates (r^*). Points represent treatment effect coefficients ($\boldsymbol{\beta_\tau}$) with 95% confidence intervals, showing how acquiring banks' rates evolve relative to control banks at each quarter relative to merger completion. Each panel corresponds to a different merger type. The specification includes bank-county-merger and time fixed effects to control for compositional changes and time-varying shocks. r^* is the residual mortgage interest rate (in percentage points) after controlling for loan and borrower characteristics and county-quarter fixed effects.

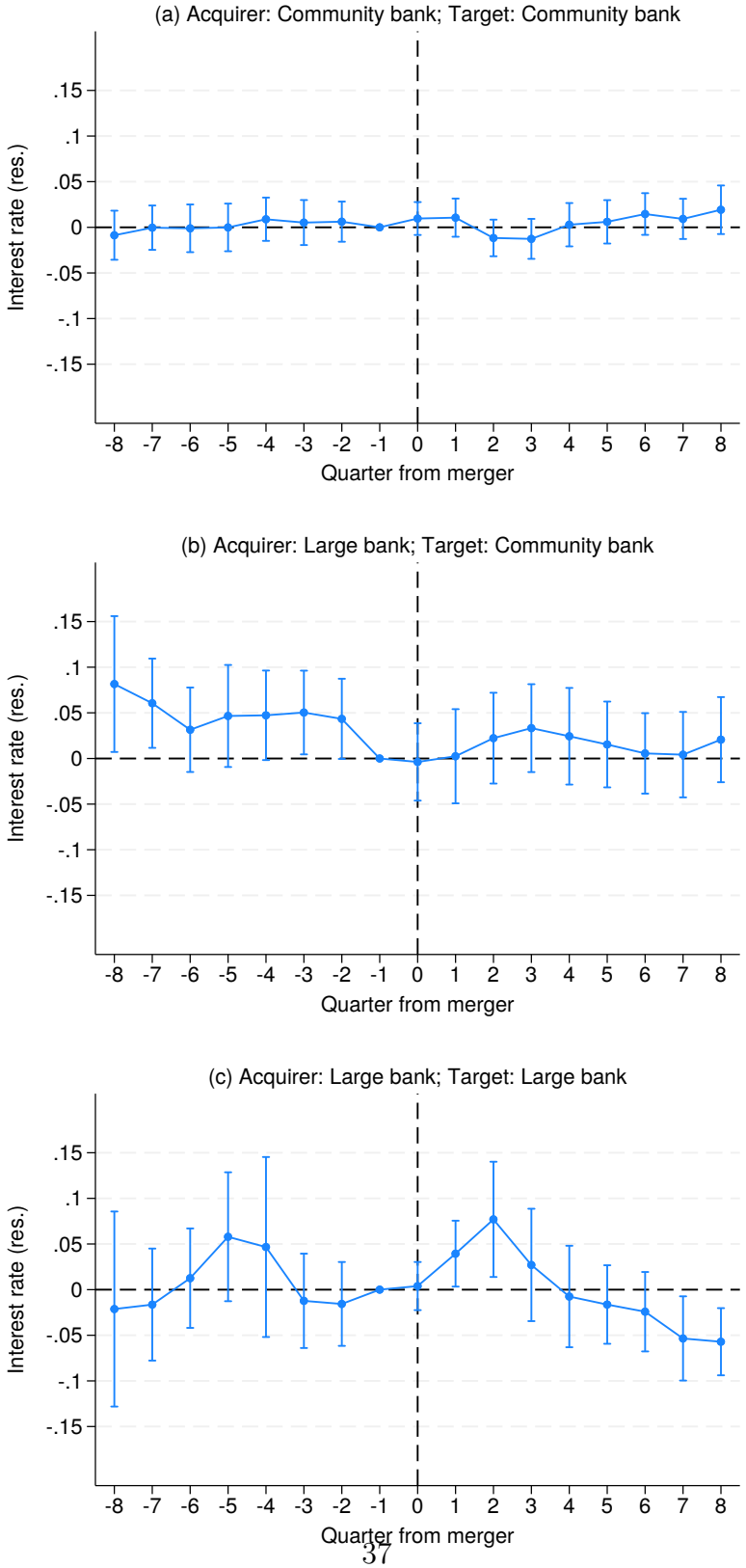


Figure 4: Average mortgage approval rates

This figure plots the evolution of average mortgage approval rates around merger events for acquiring banks (red dashed), target banks (green short-dashed), and control banks (blue solid). Each panel corresponds to a different merger type based on acquirer and target bank sizes. The vertical line at quarter zero marks merger completion. Approval rate is the fraction of mortgage applications approved by a lender in a given county-quarter.

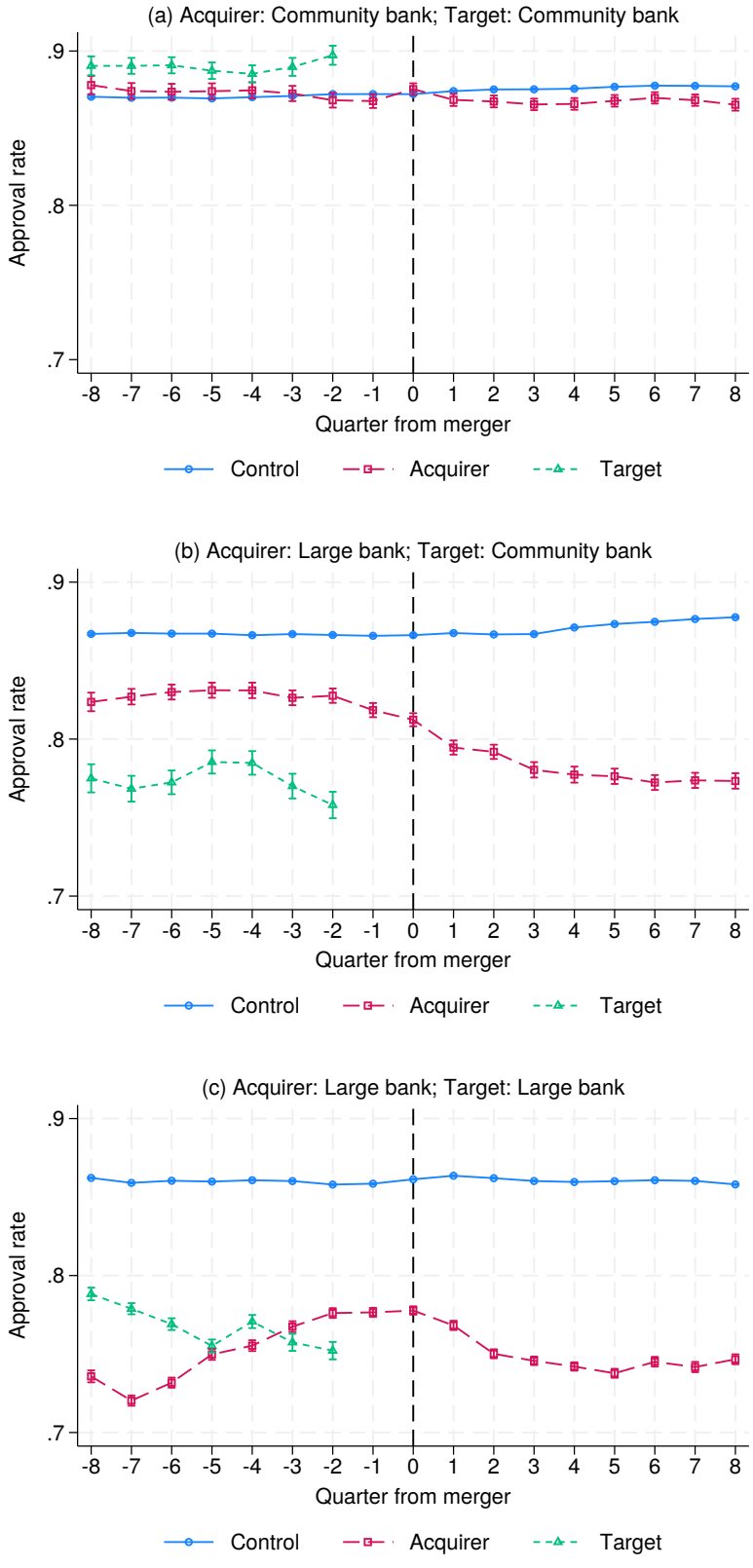


Figure 5: Stacked panel DiD – approval rates

This figure presents DiD estimates of merger effects on mortgage approval rates. Points represent treatment effect coefficients ($\boldsymbol{\beta_\tau}$) with 95% confidence intervals, showing how acquiring banks' approval rates evolve relative to control banks at each quarter relative to merger completion. Each panel corresponds to a different merger type. Approval rate is the fraction of mortgage applications approved by the lender.

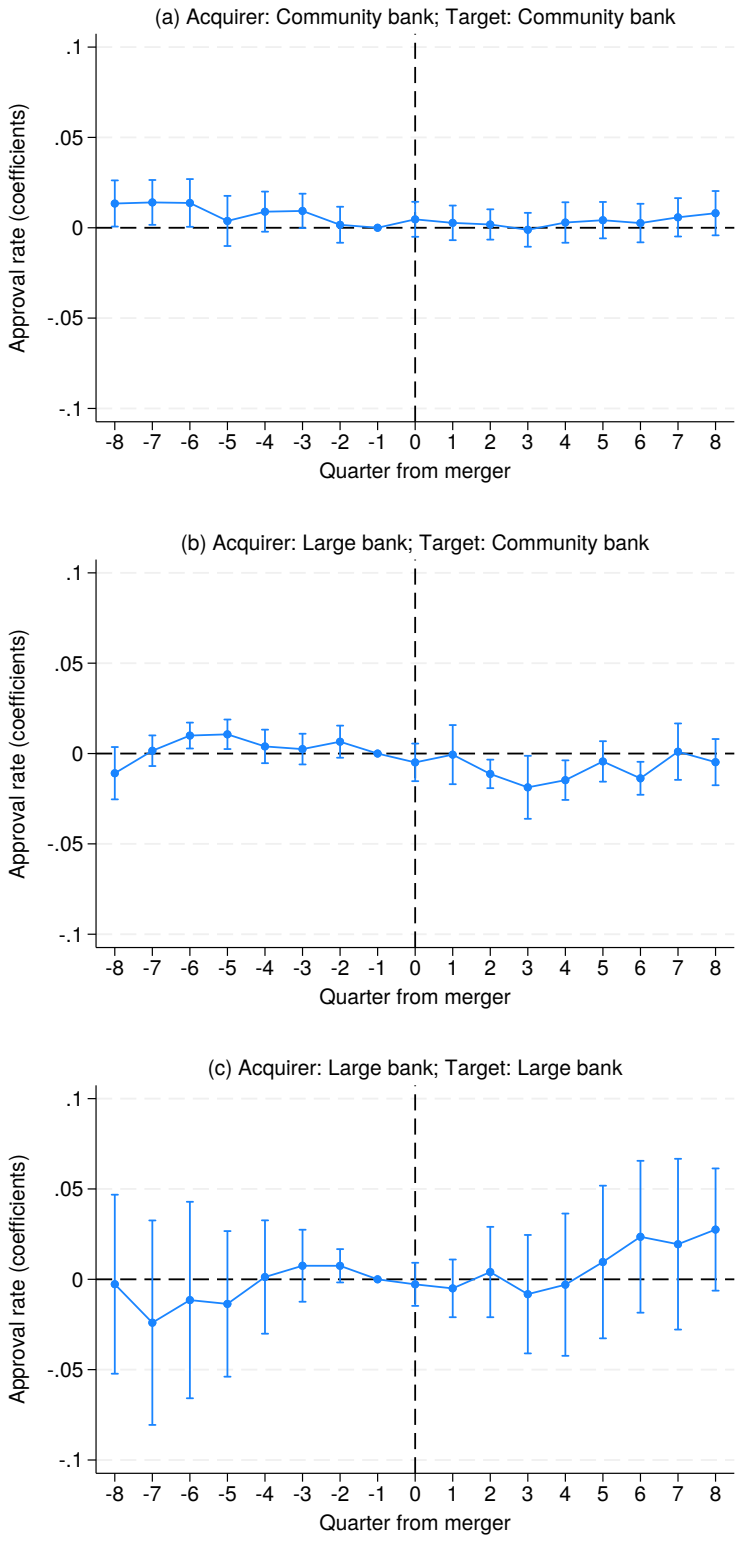


Figure 6: Average delinquency rates of newly originated mortgages

This figure plots the evolution of average delinquency rates for newly originated mortgages around merger events for acquiring banks (red dashed), target banks (green short-dashed), and control banks (blue solid). Each panel corresponds to a different merger type. The vertical line at quarter zero marks merger completion. Delinquency is defined as mortgages that become 90+ days delinquent or experience foreclosure, bankruptcy, or similar adverse outcomes at any point through the mortgage's life.

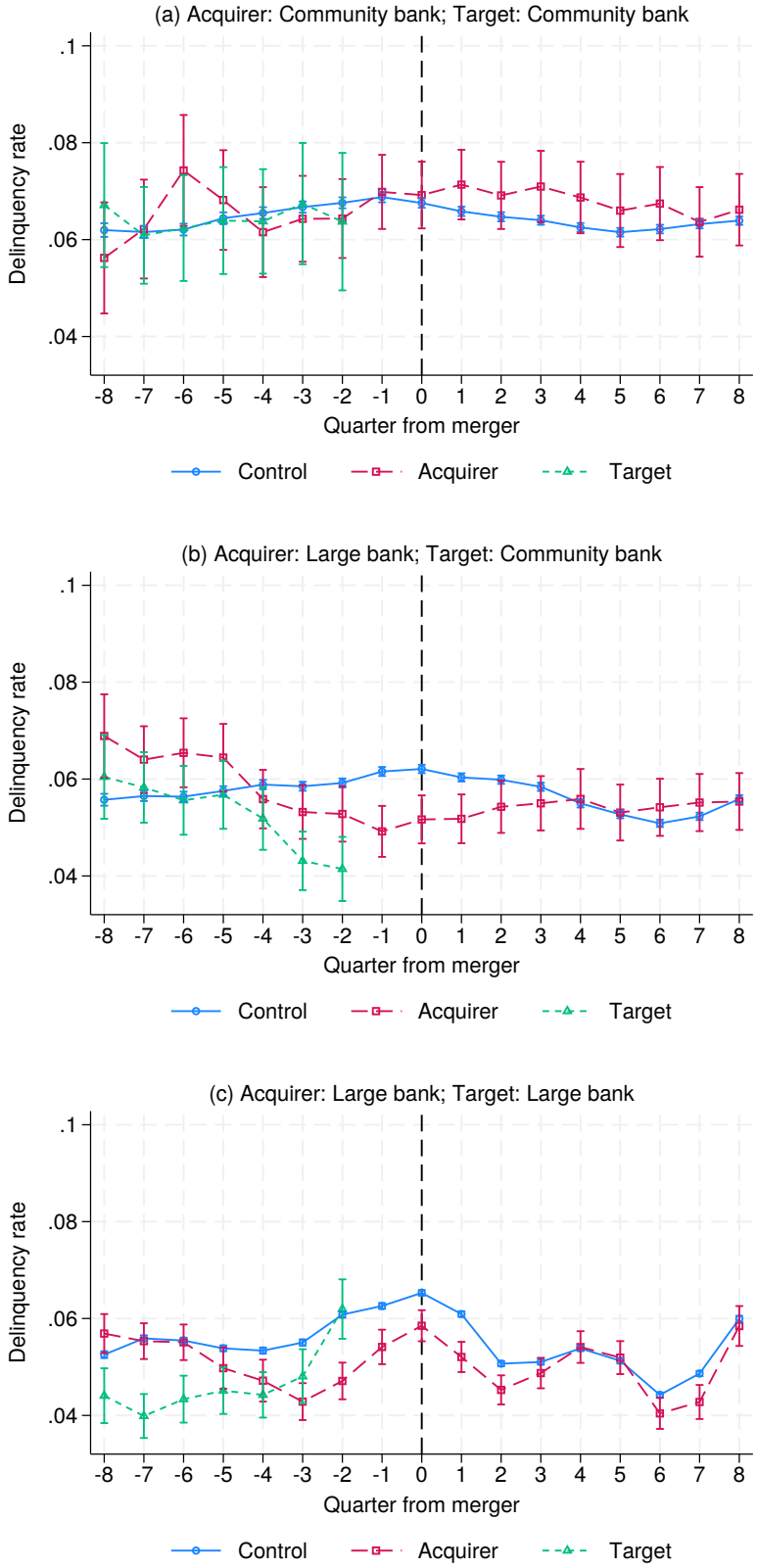


Figure 7: Stacked panel DiD – delinquency rates

This figure presents DiD estimates of merger effects on delinquency rates for newly originated mortgages. Points represent treatment effect coefficients ($\boldsymbol{\beta_\tau}$) with 95% confidence intervals, showing how acquiring banks' delinquency rates evolve relative to control banks at each quarter relative to merger completion. Each panel corresponds to a different merger type. Delinquency rate is the fraction of newly originated mortgages in a bank-county-quarter that become 90+ days delinquent or experience foreclosure, bankruptcy, or similar adverse outcomes at any point during the sample period.

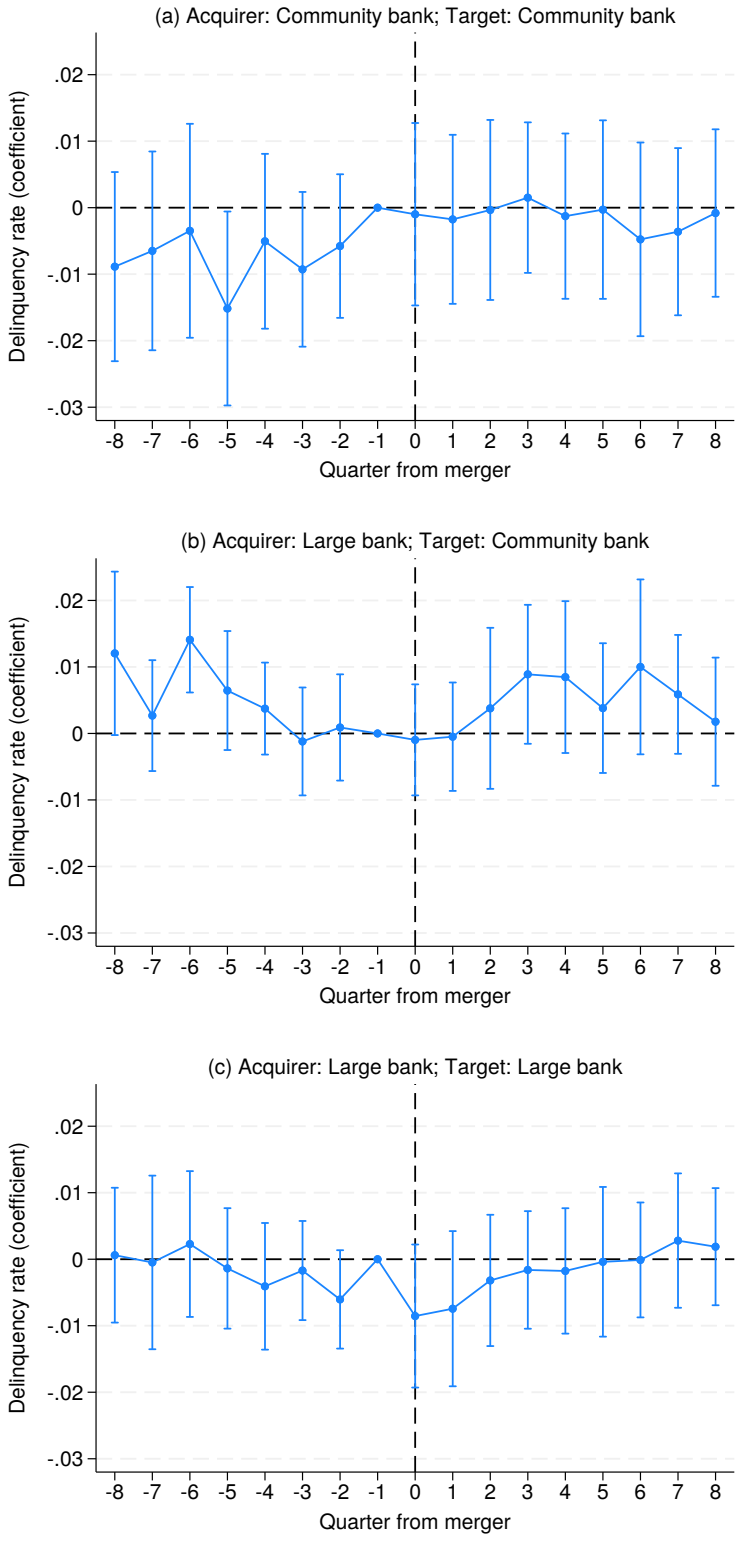
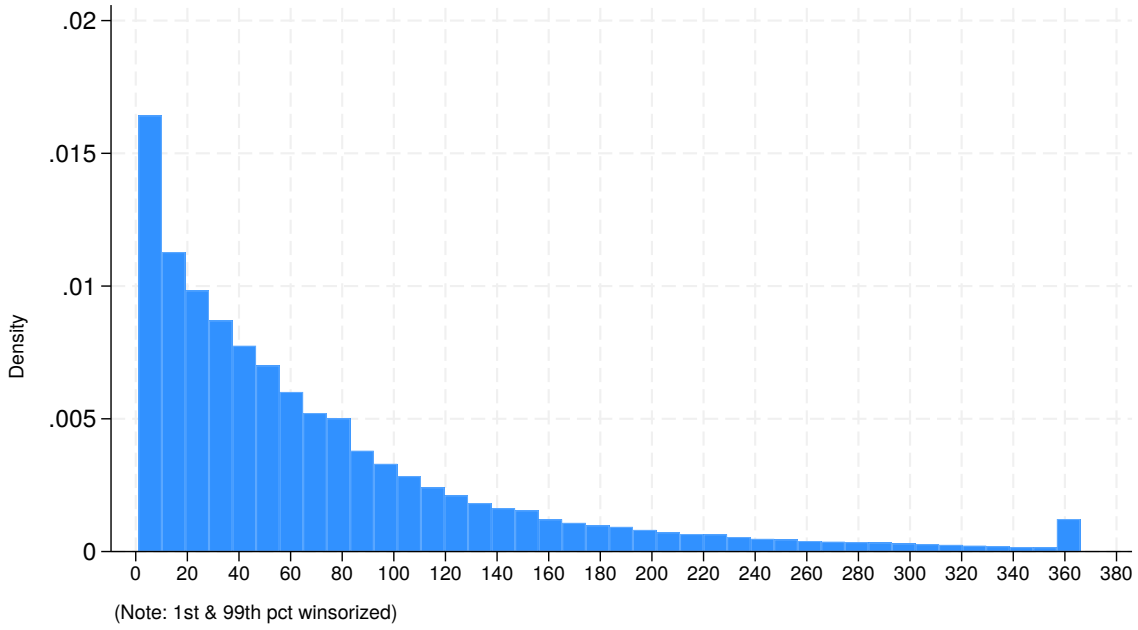


Figure 8: Distribution of mortgage lenders and market concentration across county-quarters

Panel (a) shows the distribution of the number of mortgage lenders (at parent level) operating in each county-quarter. Panel (b) presents the distribution of the HHI calculated from lender market shares at the county-quarter level. Number of lenders is the total number of distinct lenders (banks and non-banks, at the parent company level) originating at least one mortgage in a county-quarter. HHI is the Herfindahl-Hirschman Index, calculated as the sum of squared market shares (in decimal form) of all lenders in a county-quarter, scaled by 10,000 (range: 0–10,000).

(a) Number of lenders (county-quarter)



(b) HHI (county-quarter)

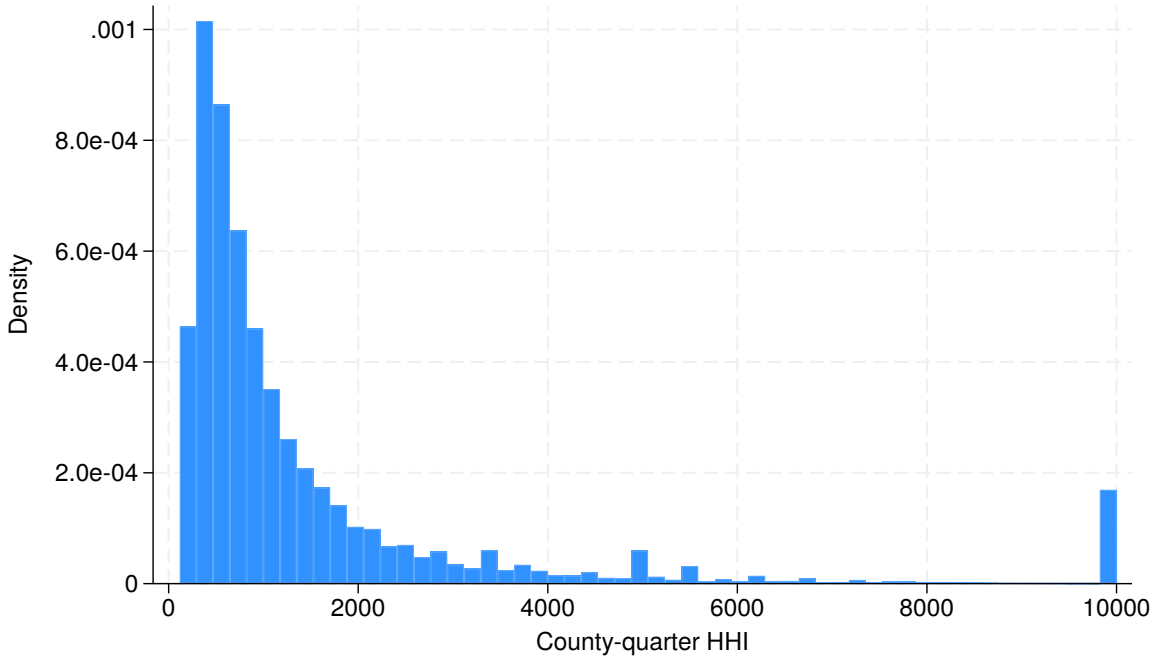


Figure 9: Geographic distribution of mortgage lenders across U.S. counties

This figure maps the number of active mortgage lenders across U.S. counties, during our sample period (averaged). Darker shading indicates a higher number of lenders. Number of lenders is the total number of distinct lenders (at the parent company level) originating at least one mortgage in a county-quarter.

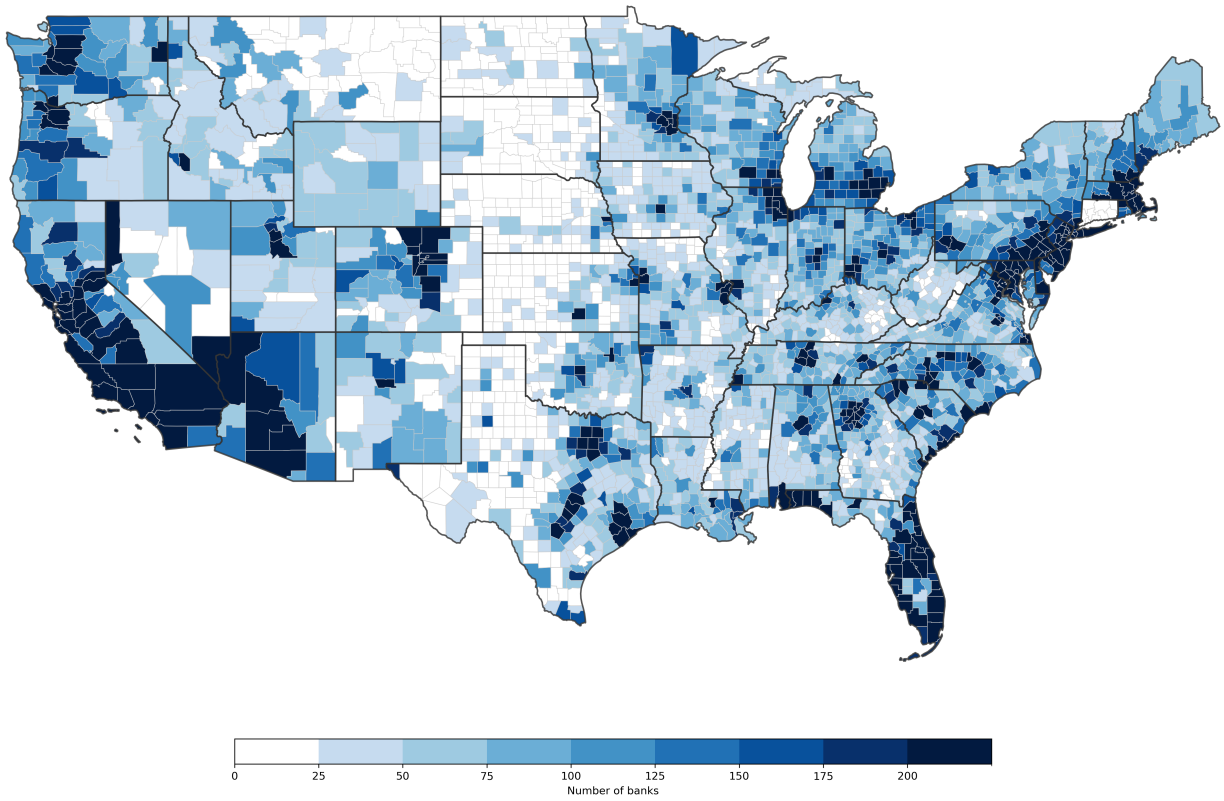
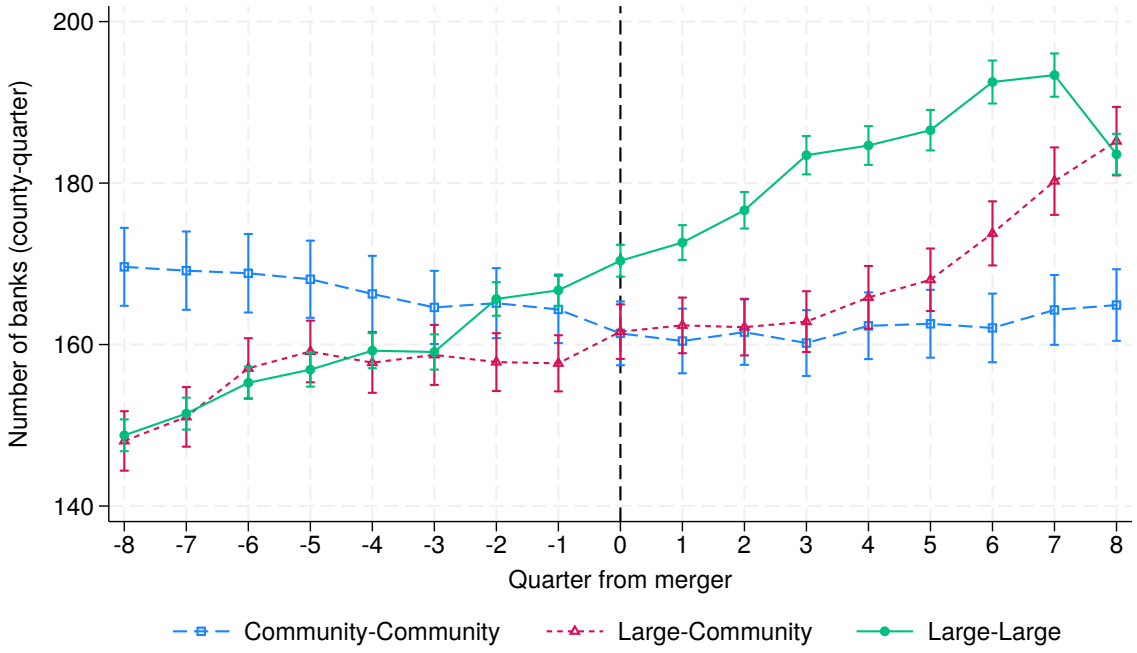


Figure 10: Evolution of market structure around bank mergers

Panel (a) shows the average number of lenders per county-quarter from 8 quarters before to 8 quarters after merger completion for three merger types. Panel (b) shows the average county-quarter HHI over the same event window. The vertical line at quarter zero denotes merger completion. Number of lenders is the count of distinct lenders (at the parent company level) active in a county-quarter. HHI is the Herfindahl-Hirschman Index, calculated as the sum of squared market shares (in decimal form) of all lenders in a county-quarter, scaled by 10,000 (range: 0–10,000).

(a) Number of lenders (county-quarter)



(b) HHI (county-quarter)

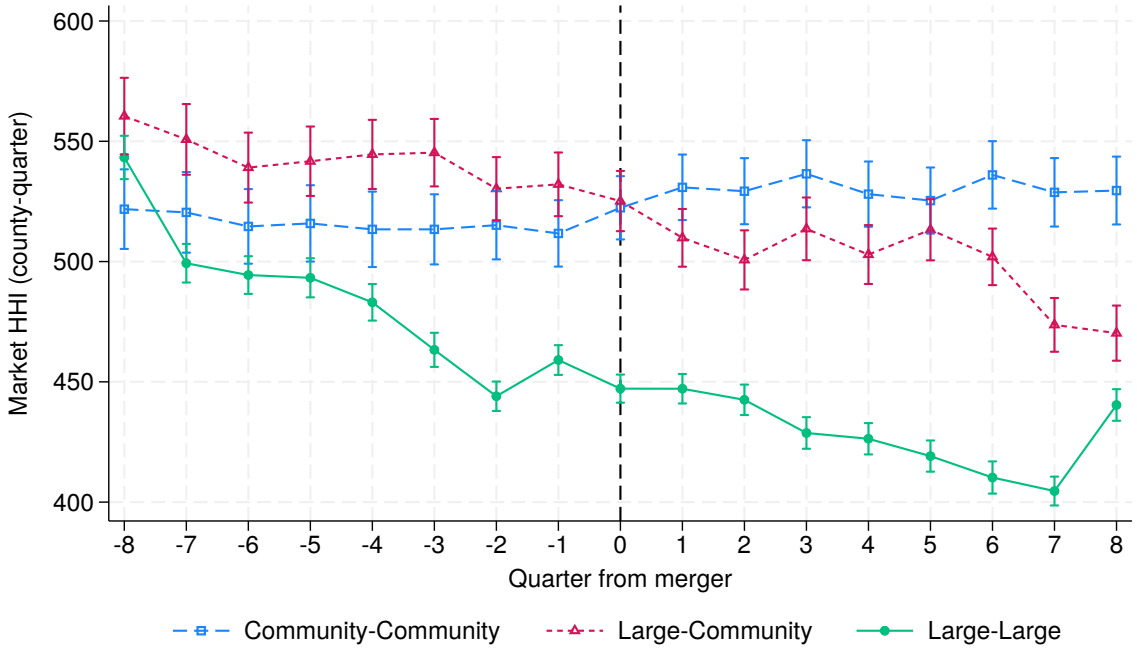


Table 1: Bank merger types by acquirer and target group

This table shows the distribution of bank mergers in our sample by acquirer and target size groups. Community banks have total assets below $10 billion; large banks (combining regional and large) have total assets above $10 billion. All thresholds are inflation-adjusted using the GDP deflator. Values show counts and percentages of mergers for each acquirer–target combination. The sample includes 4,829 mergers over 1996–2021.

	Target size		
Acquirer size	Community	Large	Total
Community bank	2,642 (55%)	— —	2,642 (55%)
Large bank	1,683 (35%)	504 (10%)	2,187 (45%)
Total	4,325 (90%)	504 (10%)	4,829 (100%)

Table 2: Market attributes by merger type

This table presents market and lending characteristics broken down by target type (Community versus Large) and acquirer type (Community versus Large), showing control, acquirer, and target banks pre- and post-merger (Pre-M/Post-M). Each cell reports the mean at the bank-county-quarter level, averaged over the 17-quarter event window (8 pre-merger quarters, the merger quarter, and 8 post-merger quarters). Variable definitions: *Int. rate (res.)* is the residual interest rate (in percentage points) after controlling for loan characteristics and county-quarter fixed effects; *Int. rate spread* is the mortgage rate minus a benchmark rate (in percentage points); *Approval rate* is the fraction of applications approved (0–1 scale); *Delinq.* is the fraction of loans ever 90+ days delinquent or in foreclosure, bankruptcy, or similar adverse status (0–1 scale); *Lender fees* are origination fees in dollars; *Approved loans* is the average number of mortgages approved per bank-county-quarter; *# of applications* is the average number of applications received per bank-county-quarter; *Bank Mkt share* is the bank's share of county-quarter mortgage originations (0–1 scale). *Number of lenders* is the average count of distinct lenders originating at least one mortgage in a county-quarter.

	Target bank type									
	Community					**Large**				
	Control		Acquirer		Target	Control		Acquirer		Target
	Pre-M	Post-M	Pre-M	Post-M	Pre-M	Pre-M	Post-M	Pre-M	Post-M	Pre-M
Acquirer bank type										
Community										
Int.rate (res.)	0.00	0.00	-0.06	-0.07	-0.04					
Int.rate spread	3.31	2.99	3.42	3.13	3.47					
Approval rate	0.87	0.88	0.87	0.87	0.89					
Delinq.	0.07	0.07	0.07	0.07	0.07					
Lender fees	1211	1270	763	946	719					
Approved loans	21	20	26	29	19					
# of applications	27	26	31	34	21					
Bank Mkt share	0.01	0.01	0.03	0.04	0.02					
Number of lenders	166	161	166	161	178					
Large										
Int.rate (res.)	-0.00	-0.00	-0.04	0.01	0.19	-0.00	0.00	0.05	-0.02	-0.07
Int.rate spread	3.10	3.07	3.16	3.23	3.50	3.18	3.12	3.55	3.27	3.31
Approval rate	0.87	0.87	0.82	0.78	0.78	0.86	0.86	0.76	0.75	0.77
Delinq.	0.06	0.06	0.06	0.06	0.06	0.07	0.07	0.07	0.08	0.07
Lender fees	1323	1311	950	1072	951	1305	1367	810	896	745
Approved loans	25	24	51	45	26	24	25	65	71	41
# of applications	32	30	64	59	36	30	32	84	94	54
Bank Mkt share	0.01	0.01	0.04	0.04	0.02	0.01	0.01	0.04	0.04	0.02
Number of lenders	161	170	161	170	167	153	163	153	163	165

Table 3: Borrower and mortgage attributes by merger type

This table presents borrower and loan characteristics by merger type, broken down by target type (Community versus Large) and acquirer type (Community versus Large), for control, acquirer, and target banks pre- and post-merger (Pre-M/Post-M). Each cell reports the mean at the bank-county-quarter level, averaged over the 17-quarter event window (8 pre-merger quarters, the merger quarter, and 8 post-merger quarters). Variable definitions: *Applicant income* is the borrower's annual gross income in thousands of dollars ($K); *LTV ratio* is the loan-to-value ratio in percent; *FICO score* is the borrower's credit score at origination (300–850 scale); *Fixed rate* is an indicator equal to one for fixed-rate mortgages; *Conventional* is an indicator equal to one for loans not insured by government agencies; *FHA loan* is an indicator equal to one for Federal Housing Administration insured loans; *Owner-occupied* is an indicator equal to one if the property is the borrower's primary residence; *Portfolio* is an indicator equal to one if the lender retains the loan rather than selling it on the secondary market. All indicators are expressed as shares (0–1 scale) when averaged.

	Target bank type									
	Community					**Large**				
	Control		Acquirer		Target	Control		Acquirer		Target
	Pre-M	Post-M	Pre-M	Post-M	Pre-M	Pre-M	Post-M	Pre-M	Post-M	Pre-M
Acquirer bank type										
Community										
Applicant income	117	127	95	94	95					
LTV ratio	78	78	79	80	79					
FICO score	735	736	735	732	735					
Fixed rate	0.94	0.96	0.97	0.98	0.97					
Conventional	0.75	0.76	0.70	0.69	0.71					
FHA loan	0.15	0.13	0.19	0.19	0.19					
Owner-occupied	0.91	0.90	0.93	0.93	0.93					
Portfolio	0.07	0.08	0.03	0.04	0.04					
Large										
Applicant income	110	119	92	100	87	98	105	89	98	99
LTV ratio	76	76	77	75	70	75	74	75	73	73
FICO score	730	735	734	735	740	722	727	724	727	724
Fixed rate	0.93	0.95	0.94	0.95	0.94	0.91	0.94	0.93	0.94	0.89
Conventional	0.79	0.79	0.78	0.81	0.84	0.80	0.82	0.83	0.84	0.86
FHA loan	0.13	0.12	0.16	0.13	0.11	0.13	0.11	0.12	0.11	0.09
Owner-occupied	0.90	0.90	0.91	0.91	0.95	0.91	0.90	0.90	0.88	0.91
Portfolio	0.07	0.08	0.09	0.15	0.41	0.07	0.08	0.09	0.08	0.14

Table 4: Local mortgage market structure

This table reports summary statistics for local mortgage market structure. Panel A presents statistics at the county-bank-quarter level (the main unit of observation in our sample), where each bank's activity within a county-quarter is one observation. Panel B presents statistics at the bank-quarter level. The sample covers 1994–2023. Variable definitions: *Number of lenders* is the count of distinct lenders (banks and non-banks) originating at least one mortgage in a county-quarter; *Lender market share* is a lender's share of county-quarter originations (%); *Top-3/5/10 share* is the combined market share (%) of the three, five, or ten largest lenders in a county-quarter; *Nonbank share* is the combined market share (%) of all non-bank lenders; *County-quarter HHI* is the Herfindahl-Hirschman Index (sum of squared market shares × 10,000); *Lenders with ≥1%/≥5% share* is the count of lenders exceeding that market share threshold; *Quarterly entry/exit rate* is the percentage of lenders entering or exiting a county-quarter; *Top lender persistence rate* is the probability (%) that the leading lender retains its top position from the prior quarter; *# of distinct markets as active lender* (Panel B) is the number of counties in which a lender originates at least one mortgage in a given quarter.

	N	Mean	SD	P10	Median	P90
Panel A: County-bank-quarter level						
Number of lenders	25,080,936	164	121	41	132	328
Lender market share (%)	25,080,936	1.53	3.97	0.03	0.39	3.61
Top-3 share (%)	25,080,936	29	12	17	26	45
Top-5 share (%)	25,080,936	39	14	24	36	57
Top-10 share (%)	25,080,936	54	15	37	52	74
Nonbank share (%)	25,080,936	28	16	4	30	46
County-quarter HHI	25,080,936	551	498	220	406	1,001
Lenders with ≥1% share	25,080,936	23	6	17	24	30
Lenders with ≥5% share	25,080,936	4	2	2	3	6
Quarterly entry rate (%)	25,080,936	10	8	4	8	16
Quarterly exit rate (%)	25,080,936	10	10	3	7	17
Top lender persistence rate (%)	25,027,786	69	46	0	100	100
Panel B: Bank-quarter level						
# of distinct markets as active lender	870,731	29	138	1	5	35

Table 5: Financial characteristics of target and acquirer banks by merger type

This table presents Call Report financial ratios for target banks (top panel) and acquiring banks (bottom panel) by merger type: (1) Community–Community, (2) Large–Community, (3) Large–Large. The unit of observation is the bank-merger, and all ratios are computed for the quarter immediately preceding the merger. The difference columns—(1)−(2), (2)−(3), and (1)−(3)—report pairwise mean differences, and significance stars denote conventional univariate test levels. Variable definitions: *Mortgages/Total Assets* is the share of total assets held as mortgages; *ROA* is net income divided by total assets; *Net Int. Income/Total Assets* is net interest income divided by total assets; *Non Interest Expense/Total Income* is non-interest operating expenses divided by total income (higher = less efficient); *Total Expense/Total Income* is the overall cost-to-income ratio; *Total Income/# of Employees* is revenue per employee ($K); *Mortgages/# of Employees* is mortgage holdings per employee ($K); *Personnel Expenses/Total Expenses* and *Personnel Expenses/Total Income* measure labor cost intensity; *Interest Expense/Total Liabilities* and *Interest Expense/Total Deposits* measure funding costs; *Delinquent Mortgages/Total Mortgages* is the share of loans that become 90+ days delinquent or enter foreclosure, bankruptcy, or similar adverse status; *Deposits/Total Assets* measures deposit funding reliance; *Deposits/Total Mortgages* is the ratio of deposits to mortgage holdings; *Total Debt/Total Assets* is the leverage ratio; *Total Data Expenses/Total Income* measures technology spending relative to income.

	Means			Differences		
	(1)	(2)	(3)	(1)-(2)	(2)-(3)	(1)-(3)
Acquirer :	Comm.	Large	Large			
Target :	Comm.	Comm.	Large			
Target financial ratios						
Mortgages / Total assets	0.192	0.180	0.189	0.012***	-0.008	0.004
ROA: Net income / Total assets	0.001	0.007	0.004	-0.006*	0.004	-0.003***
Net int. income / Total assets	0.009	0.010	0.009	-0.001*	0.002	0.001**
Non interest expense / Total income	0.898	0.723	0.644	0.175***	0.079***	0.254**
Total expense / Total income	0.952	0.874	0.818	0.078***	0.057***	0.134***
Total income / # of employees	59.318	85.169	118.928	-25.851***	-33.759*	-59.610***
Mortgages / # of employees	12.904	15.639	29.670	-2.735***	-14.031***	-16.766***
Personnel expenses / Total expenses	0.251	0.366	0.387	-0.115***	-0.021	-0.136***
Personnel expenses / Total income	0.220	0.296	0.271	-0.075***	0.024***	-0.051***
Interest expense / Total liabilities	0.005	0.007	0.008	-0.002***	-0.001**	-0.003***
Interest expense / Total deposits	0.006	0.015	0.043	-0.009**	-0.028	-0.037***
Delinquent mortgages / Total mortgages	0.005	0.017	0.007	-0.012*	0.011	-0.002
Deposits / Total assets	0.685	0.673	0.596	0.011***	0.077***	0.088***
Deposits / Total mortgages	9.049	15.075	60.494	-6.026**	-45.419**	-51.445***
Total debt / Total assets	0.893	0.895	0.901	-0.002	-0.006**	-0.008***
Total data expenses / Total income	0.052	0.033	0.016	0.018	0.017***	0.036
Acquirer financial ratios						
Mortgages / Total assets	0.187	0.195	0.191	-0.008**	0.003	-0.005
ROA: Net income / Total assets	0.003	0.004	0.004	-0.001***	-0.000**	-0.001***
Net int. income / Total assets	0.009	0.009	0.009	0.000**	0.000***	0.001***
Non interest expense / Total income	0.712	0.619	0.614	0.093***	0.005	0.098***
Total expense / Total income	0.759	0.817	0.785	-0.058	0.032**	-0.026
Total income / # of employees	63.491	74.563	97.636	-11.072***	-23.073***	-34.145***
Mortgages / # of employees	12.022	14.571	11.461	-2.549***	3.110	0.561
Personnel expenses / Total expenses	0.244	0.311	0.299	-0.068***	0.013*	-0.055***
Personnel expenses / Total income	0.202	0.249	0.235	-0.047***	0.014**	-0.033***
Interest expense / Total liabilities	0.005	0.007	0.007	-0.003***	-0.000	-0.003***
Interest expense / Total deposits	0.006	0.011	0.012	-0.005***	-0.001***	-0.006***
Delinquent mortgages / Total mortgages	0.003	0.004	0.004	-0.001	-0.000	-0.001
Deposits / Total assets	0.669	0.617	0.565	0.052***	0.052***	0.104***
Deposits / Total mortgages	5.947	6.761	5.235	-0.814	1.526	0.712*
Total debt / Total assets	0.893	0.906	0.908	-0.013***	-0.002	-0.015***
Total data expenses / Total income	0.028	0.015	0.011	0.013***	0.004*	0.017***
Observations	2642	1683	504	4325	2187	3146

Online Appendix

"Does Banking Consolidation Harm Households?"

OA.1. Data construction appendix

This appendix provides technical details on data matching, sample construction, and variable definitions that supplement Section 2 of the main text.

OA.1.1. cHMDA–McDash matching procedure

The cHMDA and McDash datasets share no common loan identifiers. We link them using a probabilistic matching algorithm exploiting loan characteristics and timing.

Initial matching. We restrict attention to approved cHMDA applications and search for McDash loans originated in the same month and county with loan amounts within narrow tolerance bands. Before 2018, amounts must match within $500 (reflecting dollar-level recording precision). From 2018 onward, when amounts are recorded in thousands, we tighten the tolerance to $10 in the transformed scale.

Multi-factor ranking. When multiple candidates exist, we rank them by (i) the absolute difference between application and loan amounts and (ii) temporal proximity between application and closing dates. From 2018 onward, we prioritize amount differences over timing given improved recording precision.

Duplicate resolution. We resolve many-to-one and one-to-many linkages iteratively: sort all potential matches by rank score, then sequentially retain each match only if neither the application nor the loan has been previously assigned. Indicator variables flag records with multiple potential matches, enabling sensitivity analysis.

After resolution, we merge McDash loan characteristics—initial interest rate, LTV ratio, credit score, loan term, property type—and forward-looking performance indicators (90+ day delinquency, bankruptcy, foreclosure) onto matched records. The procedure yields approximately 75 million matched applications. After data quality filters (Section OA.1.5), the final matched dataset contains approximately 62.6 million loans.

Interest rate extraction. McDash records current interest rates that may reflect post-origination modifications. To recover the original contract rate, we identify the first non-missing rate observation for each loan within a three-year window of the closing date. This yields over 174 million mortgages with valid origination interest rates in the raw McDash data. Loans are also classified as GSE-backed or portfolio-held based on investor type indicators.

Lender identifier construction. cHMDA identifies lenders through systems that evolved over the sample period: earlier years use respondent identifiers from regulatory agencies; later years incorporate a universal legal entity identifier. These correspond to individual banking charters, so a single parent company may have multiple identifiers. Using Robert Avery's crosswalk files, we map charter-level identifiers to parent bank holding companies, producing consolidated lender identifiers that change only when ownership genuinely transfers through mergers or acquisitions.

OA.1.2. Bank size classification

Bank size is measured by total assets in the quarter before the merger, following Dodd-Frank thresholds with GDP-deflator adjustments: community banks have assets below $10 billion, regional banks between $10 billion and $100 billion, and large banks above $100 billion.[28]

For the main analysis, regional and large banks are consolidated into one category. Under the three-way classification, acquirers comprise 2,642 community, 1,924 regional, and 263 large banks; targets comprise 4,325 community, 490 regional, and 14 large banks, spanning 2,683 counties. Under the two-way classification used in the main text, the sample comprises 2,642 community and 2,187 large bank acquisitions.

OA.1.3. Merger event filters

We apply the following filters to identify mergers suitable for analysis (see also Section 2):

1. **Active mortgage presence.** Targets must maintain positive market share in at least one county during the two years preceding the acquisition.
2. **Financial crisis exclusion.** We exclude mergers completed during 2007Q1–2009Q4, as lending behavior during this period reflects extraordinary circumstances.
3. **Acquirer pre-merger presence.** We drop merger-county combinations where the acquirer lacks pre-merger market share, avoiding confounds from simultaneous market entry.
4. **Overlapping mergers.** We exclude counties experiencing multiple merger events within the 17-quarter event window (8 pre, merger quarter, 8 post), applied recursively. For each target-county pair, we search forward from the merger date; if a subsequent merger involving a bank active in that county occurs within eight quarters and involves targets above the county's fiftieth-percentile market share, we exclude that county-merger combination.
5. **Clean control group.** Control banks must not experience any merger in the county during the 17-quarter window. Non-banks are excluded from the control group.

OA.1.4. Market share and concentration construction

For each lender-county-quarter, we compute:

- *Market share*: the fraction of approved loans (count) originated by a specific lender in a given county-quarter relative to total approved loans in that county-quarter.
- *Market ranking*: ordinal and percentile positions in the local distribution.
- *Trailing four-quarter moving averages* of shares and rankings to smooth temporary fluctuations—particularly valuable when characterizing pre-merger market positions.

County-quarter concentration is measured by the Herfindahl-Hirschman Index:

$$HHI_{c,t} = \sum_{i=1}^{N_{c,t}} (s_{i,c,t})^2 \times 10{,}000 \tag{3}$$

[28] For robustness, we apply alternative pre-2005 thresholds of $1 billion (community) and $50 billion (large), since the deflator yields a 1994 community threshold of approximately $6 billion. Results are robust.

where $s_{i,c,t}$ is the market share of lender i in county c at time t and $N_{c,t}$ is the number of active lenders.

OA.1.5. Data quality filters

Geographic and institutional restrictions. We restrict the sample to the fifty states and the District of Columbia, drop observations with missing or invalid county codes, and exclude non-banks from the control group.

Loan-level filters. We require approved loan amounts to exceed \$10,000, exclude interest rates below 0.5 percent, and drop records missing any of: interest rate, applicant income, LTV ratio, FICO score, loan amount, maturity, rate type, mortgage type, occupancy type, or repayment status. Continuous variables are winsorized at the 1st and 99th percentiles. The final sample contains approximately 44.3 million mortgages (1994–2023).

OA.1.6. Variable construction

Residualized interest rates (r^*). See Equation (1) in the main text. We regress raw mortgage rates on borrower and loan characteristics and county×quarter fixed effects; the residual r^* (in percentage points) is our primary price measure. Several alternative specifications with different control sets and fixed effects structures are used for robustness. We also compute the spread between the mortgage rate and the Federal Funds rate and obtain qualitatively similar results.

Approval rates. The ratio of approved applications to total applications for each lender-county-quarter. Date formats are standardized across years to account for evolving reporting conventions.

Delinquency rates. The fraction of originated loans that become 90+ days delinquent or experience foreclosure or bankruptcy at any point during their life, computed at the lender-county-quarter level.

Panel datasets. We construct two complementary datasets:

1. A *loan-level dataset* where each observation is a single mortgage augmented with the lender's market position and merger involvement.
2. A *lender-county-quarter dataset* in which loan-level variables are averaged within each cell. Both simple and residualized means are computed.

OA.2. Additional results

This section presents supplementary figures and tables referenced in the main text:

- Figure OA.1: plots average lender fees for acquirers, targets, and control banks across the event window, separately by merger type, to document raw fee dynamics around mergers.
- Figure OA.2: reports stacked difference-in-differences estimates of merger effects on lender fees, showing treatment effect coefficients at each quarter relative to merger completion.
- Figure OA.3: presents pre-merger distributions of residualized mortgage rates for acquirers, targets, and control banks across merger types, as well as pre- versus post-merger comparisons for acquirers, highlighting the cross-sectional pricing differences that underlie composition effects in simple pre-post comparisons.
- Table OA.1: reports the minimum number of distinct banks underlying each figure and table in the paper, ensuring that no result is driven by a small number of institutions.
- Table OA.2: shows the full three-way distribution of mergers by acquirer and target size group (community, regional, large), complementing the two-way classification used in the main analysis.
- Table OA.3: provides county-quarter-level summary statistics on local mortgage market structure, including concentration measures, lender counts, entry/exit rates, and top-lender persistence.

Figure OA.1: Average lender fees around bank mergers

This figure plots the evolution of average lender fees around merger events for acquiring banks (red dashed), target banks (green short-dashed), and control banks (blue solid). Each panel corresponds to a different merger type based on acquirer and target bank sizes. The vertical line at quarter zero marks merger completion. Lender fees are fees charged by the lender for processing and underwriting the mortgage, excluding third-party costs.

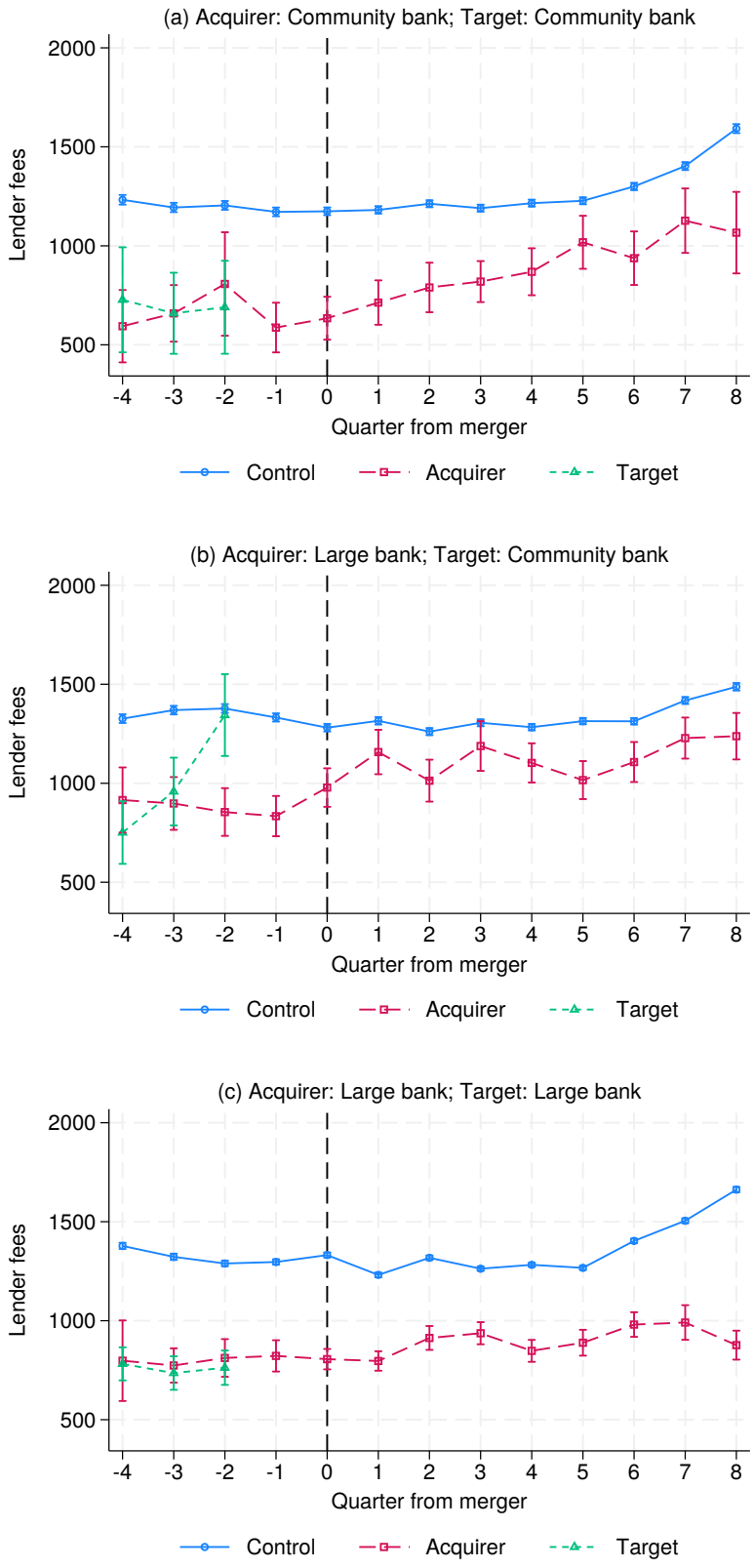


Figure OA.2: Stacked panel DiD – Lender fees

This figure presents DiD estimates of merger effects on lender fees. Points represent treatment effect coefficients ($\boldsymbol{\beta_\tau}$) with 95% confidence intervals, showing how acquiring banks' lender fees evolve relative to control banks at each quarter relative to merger completion. Each panel corresponds to a different merger type. The specification includes bank-county-merger and time fixed effects. Lender fees are fees charged by the lender for processing and underwriting the mortgage, excluding third-party costs.

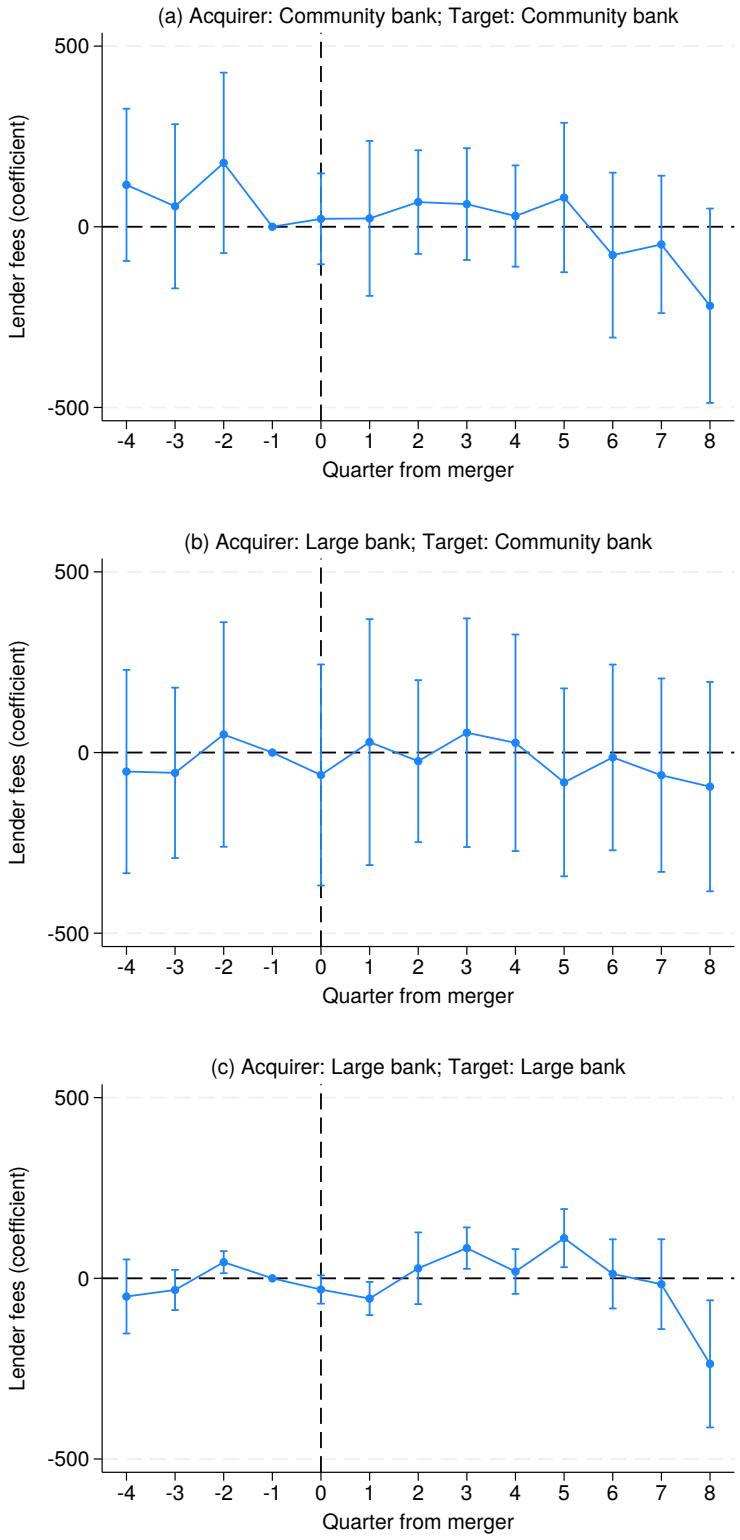


Figure OA.3: Pre-merger and pre-vs-post-merger rate distributions across bank types

This figure presents empirical cumulative distribution functions (ECDFs) of residualized interest rates (r^*). Panels (a) and (c) compare the pre-merger distributions of control banks (blue dashed), target banks (red solid), and acquiring banks (green solid), separately by merger type. Panels (b) and (d) compare the pre-merger (blue dashed) and post-merger (red solid) distributions for acquiring banks only, separately by merger type. If acquirers changed their pricing strategies post-merger, the pre- and post-merger distributions in panels (b) and (d) would diverge. r^* is the residual mortgage interest rate (in percentage points) after controlling for loan and borrower characteristics and county-quarter fixed effects.

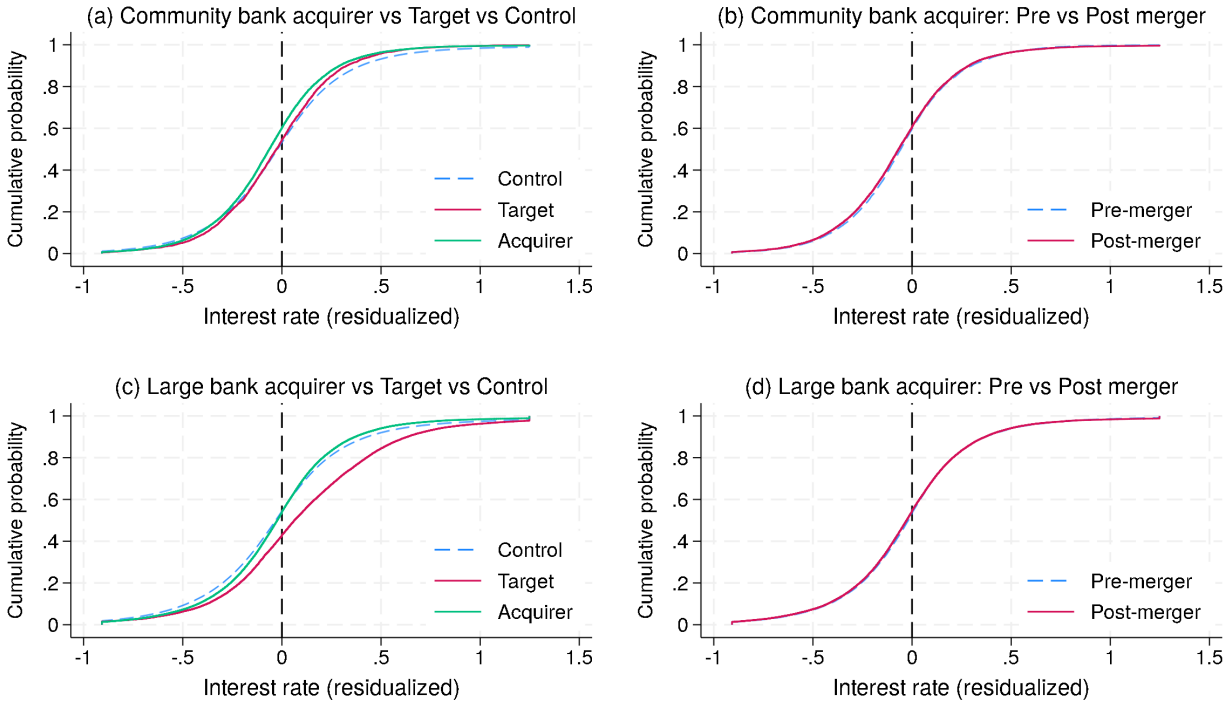


Table OA.1: Minimum number of distinct banks in each figure and table

This table reports the minimum number of distinct banks underlying each figure and table in the paper. For event study figures, the minimum is taken across all event-time quarters (−8 to +8). For summary statistics tables, the minimum is reported separately by group (control, acquirer, target) and period (pre-merger, post-merger). Banks are counted at the parent company level.

Figure/Table	Panel / Group	Period	Min. Banks
Figures 2, 4, 6, OA.1: Levels event studies			
	Community–Community		1,302
	Large–Community		511
	Large–Large		198
Figures 3, 5, 7, OA.2: Stacked panel DID			
	Community–Community		9,453
	Large–Community		9,981
	Large–Large		11,022
Figure 10: Pre/post-merger market structure			
	Community–Community		721
	Large–Community		227
	Large–Large		87
Tables 2 & 3: Attributes by merger type			
Community–Community mergers			
	Control	Pre-merger	9,949
	Control	Post-merger	9,189
	Acquirer	Pre-merger	1,030
	Acquirer	Post-merger	956
	Target	Pre-merger	1,138
Large–Community mergers			
	Control	Pre-merger	10,938
	Control	Post-merger	10,103
	Acquirer	Pre-merger	481
	Acquirer	Post-merger	354
	Target	Pre-merger	997
Large–Large mergers			
	Control	Pre-merger	11,976
	Control	Post-merger	11,126
	Acquirer	Pre-merger	186
	Acquirer	Post-merger	155
	Target	Pre-merger	396

Table OA.2: Bank merger types by acquirer and target group

This table shows the distribution of bank mergers in our sample by acquirer and target size groups. Community banks have total assets below $10 billion, regional banks have total assets between $10 billion and $100 billion, and large banks have total assets above $100 billion. All thresholds are inflation-adjusted using the GDP deflator. Values show counts and percentages of mergers for each acquirer–target combination. The sample includes 4,829 mergers over 1996–2021.

	Target Group			
Acquirer Group	Community	Regional	Large bank	Total
Community bank	2,642 (55%)	0 (0%)	0 (0%)	2,642 (55%)
Regional bank	1,593 (33%)	331 (7%)	0 (0%)	1,924 (40%)
Large bank	90 (2%)	159 (3%)	14 (0%)	263 (5%)
Total	4,325 (90%)	490 (10%)	14 (0%)	4,829 (100%)

Table OA.3: Local mortgage market structure: county-quarter level

This table reports summary statistics for local mortgage market structure at the county-quarter level, where each county-quarter is one observation. Variables include concentration measures (top-k lender shares, HHI), the nonbank market share, lender counts (total and by market share thresholds), quarterly entry and exit rates, and top lender persistence (the probability that the leading lender in a county retains its top position in the following quarter). The sample covers 1994–2023.

	N	Mean	SD	P10	Median	P90
Number of lenders	384,776	75	79	9	50	174
Lender market share (%)	384,776	5.85	12.10	0.14	1.56	15.08
Top-3 share (%)	384,776	43	21	21	38	74
Top-5 share (%)	384,776	54	21	30	50	89
Top-10 share (%)	384,776	70	19	45	68	100
Nonbank share (%)	384,776	28	20	2	27	51
County-quarter HHI	384,776	1,185	1,274	308	745	2,562
Lenders with $\geq$1% share	384,776	20	8	7	20	29
Lenders with $\geq$5% share	384,776	5	2	2	4	7
Quarterly entry rate (%)	384,776	13	12	3	10	25
Quarterly exit rate (%)	384,776	11	12	1	9	22
Top lender persistence rate (%)	382,598	62	49	0	100	100