Do Small Bank Failures Reduce Local Mortgage Lending and Household Access to Credit?

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Abstract:

This paper examines whether local bank failures reduce household access to mortgage credit in the United States. Using county-level data from 2007 to 2017, this paper combined FDIC bank failure records with Home Mortgage Disclosure Act (HMDA) mortgage data to study how mortgage denial rates change following a bank failure. The analysis employs a difference-in-differences framework that compares counties before and after a bank failure to counties without a failure in the same year, controlling for county and year fixed effects as well as local economic and demographic conditions. The study finds that bank failures are initially associated with higher mortgage denial rates, but this relationship becomes small and statistically insignificant once broader economic factors are taken into account. However, failures involving larger banks, measured by total failed assets, are linked to modest increases in denial rates. Overall, the results suggest that while large bank failures can disrupt local mortgage markets, broader economic conditions play a more important role than bank failures themselves in shaping household access to mortgage credit.

1. Introduction

When a small community bank suddenly fails and closes, residents may find it difficult to begin the process of owning a home. Mortgage applications may slow, approval rates drop, and the processing becomes overall tougher. This research investigates whether or not such bank failures restrict households' access to mortgage credits in the communities in which they reside. While this may seem intuitive—fewer local banks mean fewer places to get a loan—the mechanisms are more complex. Even households with previously strong credit histories may face delays or increased scrutiny, and the effects can ripple through the local economy. The hypothesis central to this study is that counties heavily exposed to bank failures will see a measurable decline in mortgage approvals. Mortgages are not just vital for big-ticket purchases; they help to mobilize local construction, spending, and home-value stability. According to the National Community Reinvestment Coalition, non-bank mortgage companies now originate 53.3% of all home loans, while banks' share has fallen from 42.5% in 2018 to just 30.1% in 2024. This highlights how in today's age, banks still play a substantial–but shrinking– role in home lending, especially in areas underserved by nonbank lenders.

In order to test this hypothesis I combine the FDIC Failed Bank List and FDIC Summary of Deposits data (insights into which counties relied heavily on a failing bank) with HMDA microdata, providing loan-level detail from the past 20 years. I then measure how much each county relied on a failing bank based on the total assets of the failed bank, then use an event-study and difference-in-differences approach to see how mortgage activity and approval rates changed. I expect to find that counties most exposed to a failing bank experience sharp declines in origination rates and increased denial rates, with some rebound, as non-bank lenders step into the void, but likely not fully making up for the local bank's absence.

2. Literature Review

The question of interest is how bank failures affect counties' access to credit. Current research shows that bank failures hurt local economies mainly by disrupting credit supply. Historical studies like Bernanke (1983) and Grossman (1993) found that banking crises cut off lending, ultimately leading to lower investment, output, and demand. The work of Calomiris, Hubbard, and Stock (1987) and Gilbert and Kochin (1989) confirmed these effects in rural areas, where bank closures reduced sales, and activity. Kandrac (2014) used county-level data to show slower income growth, weaker employment, and higher poverty after a bank failure. Even in more modern times with FDIC insurance, Nguyen (2019) found similar results, that included lower small business lending and hindered wage growth. Overall, local banks and their stability are essential for healthy economic performance and raises questions and concerns about how they affect an individual household's ability to receive credit.

One of the key reasons why bank failures matter is because of the loss of lending relationships. Banks build personal relationships with borrowers, creating trust that is extremely hard to replace. Agarwal et al. (2009) show how these relationships lower default risk and shape credit availability over the business cycle (Boualam and Mazet-Sonilhac (2020)). Kandrac (2014) found that local communities are less harmed by failures when resolution strategies preserve the relationship between borrowers and their bank. International evidence from Jiangli, Unal, and Yom (2024) confirms that firms with strong banking relationships survive stress more easily. Together, this evidence highlights that the main channel through which bank failures weaken economies is through the disruption of local relationships, with direct implications for household mortgage access.

Bank failures also matter in the mortgage industry because household banking remains local. Amel and Starr-McCluer (2008) showed that community banks are still central to mortgage origination, while Gao, Wu, and Zhang (2023) found that branch manager experience influences approval decisions. When branches close, these outcomes can change directly, with nonbank lenders and fintech firms partly filling the gap. Research shows that they expand access and improve technological services for underserved borrowers (Degerli and Wang 2022; Begley and Srinivasan 2023; Jagtiani and Chernoff 2023), but they do not fully replace the role of local banks. Kandrac (2014) and Nguyen (2019) stress that the severity of disruption really depends on local exposure and how closures are managed. Even with new financing alternatives, broader economies, like the mortgage market, remain vulnerable to local bank failures.

Despite there being strong evidence about how bank failures disrupt local economies and weaken lending, less is known about their direct impact on household mortgage access. Most studies thus far focus on firm lending or aggregate economic indicators, while household level consequences remain unexplored. In particular, we lack clarity on whether small bank failures uniquely constrain mortgage credit in ways that nonbank lenders or fintech substitutes cannot offset. Addressing this gap is essential for understanding how local banking shocks translate into household financial vulnerability, and directly brings up the question of whether small bank failures reduce local mortgage lending and household access to credit.

3. Theory

Theoretically, the effect of a bank failure can be illustrated within a simple supply-and-demand framework for mortgage lending. Household demand for mortgages tends to be stable in the short run and is driven by factors such as income, demographics, and local housing conditions. While mortgage demand is unlikely to change immediately when a single bank closes, larger financial shocks could reduce household income and in the end lower demand. Additionally, the failure of a local bank may affect borrower confidence, making households more cautious about taking on new loans. On the supply side, the closure directly reduces mortgage lending capacity. Mortgage credit in a county typically comes from both community banks and nonbank lenders, so total supply depends on lending from both sources. When a community bank fails, the loans it would have made disappear, shifting the mortgage supply curve to the left. This combined effect is illustrated in Figure 1 below.

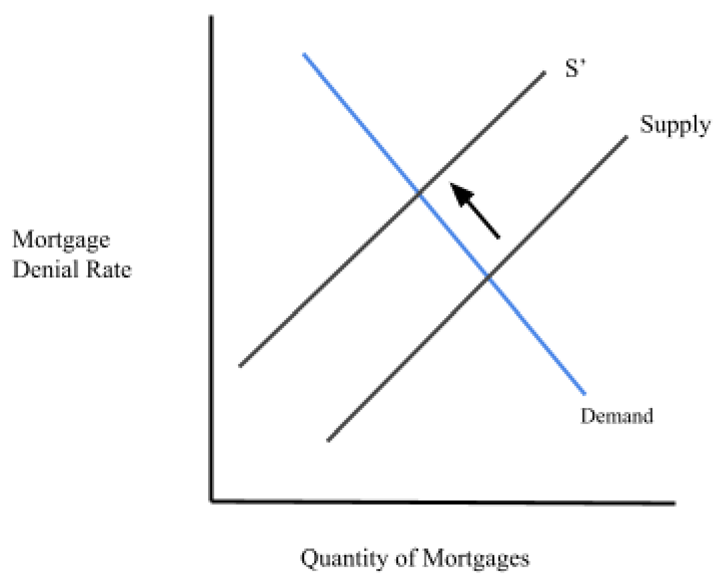

*Figure 1

The direct implication of this supply shock is a decline in the equilibrium quantity of mortgages in the affected county. Borrowers who had initially relied on the failed bank may not immediately find an alternative lender, especially those who relied on the bank's local knowledge to get approved. Approval rates are therefore expected to fall. Even applicants with strong credit histories may experience delays or denials because alternative lenders require more documentation or even take time to establish loan channels within the community. The marginal borrowers, the ones highly depending on local banks, are exactly the individuals most vulnerable to consequences from a failure.

4. Empirical Theory

The empirical strategy tests whether the theoretical mechanisms translate into measurable changes in mortgage outcomes. In particular, the analysis examines whether bank failures increase mortgage denial rates at the county level. The main hypothesis is that when a local bank fails, the resulting reduction in credit supply raises the likelihood that households are denied a mortgage. The key independent variable is the lagged number of bank failures in each county per year. Using a one-year lag captures the effect of the previous year's financial disruption on current lending and reduces concerns about reverse causality (for example, that high denial rates might contribute to bank distress). The dependent variable is the mortgage denial rate, measured in levels for ease of interpretation.

The empirical strategy employs a difference-in-differences approach that compares changes in mortgage denial rates within counties before and after a bank failure to contemporaneous changes in counties that do not experience a failure in the same year. Counties that experience a bank failure form the treatment group, starting in the year following the failure, while counties without a failure in that given year serve as the control group. Importantly, control counties may experience failures in other years. The identification comes from comparing treated counties to counties that are untreated at the same point of time.

County fixed effects absorb all time-invariant differences across counties, while year fixed effects capture nationwide shocks to mortgage markets. As a result, identification relies on within-county changes in denial rates following a bank failure, relative to changes observed in other counties during the same year.

Monetary variables—loan amount, applicant income, population, and median household income—are log-transformed to address skewness and allow coefficients to be interpreted as elasticities. Other percentage-based variables, such as unemployment, minority share, and the federal funds rate, enter in levels. County fixed effects control for all time-invariant features of each county, including geography and long-run economic structure, while year fixed effects absorb national macroeconomic shocks and regulatory changes. This design isolates within-county variation over time, providing a more credible estimate of the impact of bank failures on mortgage denial rates.

The resulting empirical model is:

$$\text{DenialRate}_{i,t} = \beta 1 \text{lag\_fail}_{i,t} + \beta 2 \ln(\text{LoanAmount}_{i,t}) + \beta 3 \ln(\text{ApplicantIncome}_{i,t}) + \beta 4 \ln(\text{TotalLoans}_{i,t}) + \beta 5 \ln(\text{Population}_{i,t}) + \beta 6 \text{MinorityPct}_{i,t} + \beta 7 \ln(\text{MedianIncome}_{i,t}) + \beta 8 \text{UnemploymentRate}_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}$$

The main identifying assumption of the difference-in-differences design is that, absent a bank failure, counties that experience a failure would have followed the same trend in mortgage denial rates as counties that did not experience a failure in that year. This is the parallel trends assumption and is made more plausible by including county and year fixed effects. The inclusion of county-level economic and demographic controls helps account for time-varying local conditions that may be correlated with both bank failures and mortgage outcomes.

5. Data Section

This study aims to examine the relationship between the number of failed banks and mortgage denial rate at the county level across the United States from the years 2007-2017. The analysis involved combining data from multiple sources to construct a finalized data set that captured local bank distress and mortgage lending outcomes over time.

The primary data on bank failures was obtained from the Federal Deposit Insurance Corporation (FDIC), which maintains detailed records on all U.S. bank failures. From this data set there were several key variables constructed at the county-year level, including a primary explanatory variable of whether or not a county had a failed bank, the total number of failed banks, the total assets of failed banks, the total deposits of failed banks, and the estimated loss associated with the failed bank.

Mortgage-level data was obtained from the Home Mortgage Disclosure Act (HMDA) microdata. Each annual HMDA data set contains millions of different observations, which are the individual loan application records submitted by financial institutions nationwide. To make the data analytically manageable and align it with the county-level framework, there were several cleaning and transformation steps undergone in STATA. One of the primary variables in the HMDA data is the variable action taken, with corresponding numbers that mean different things based on the outcome of the loan. The number of interest in this study was the number 3 which signified that the loan application was denied by the financial institution. A binary variable was created, denied, that equaled 1 if the variable action taken was equal to 3, and 0 otherwise. Another cleaning step that was undertaken was collapsing the data by county to compute aggregate denial rates which ended up being the mean of the newly created binary variable. In addition to the denial rate, there were multiple different variables retained: average loan amount, average applicant income, and total number of loans issued per county. After computing these county-level aggregates, the datasets were appended from 2007–2017 into one combined panel. Finally, the resulting data was merged with the FDIC bank failure data by matching state, county, and year.

Instead of splitting the sample by loan outcome, county-level economic and demographic controls were added to better capture differences in borrower characteristics and local economic conditions. These variables include the federal fund interest rates, county unemployment rate, annual population estimates, minority population levels and shares, and median household income. By incorporating these variables, the study was able to better account for changes in local demand for credit and demographic shifts that can inherently introduce noise into the denial rate.

Table 1 presents summary statistics for the majority of key variables in the sample. It reports the mean, standard deviation, minimum, and maximum values for the variables across all counties and years. For example, counties had an average loan amount of $134,420 with an average applicant income of $81,300, while the mean denial rate was 22%. Median household values averaged $45,939, and the minority population represented about 13.9% on average.

Summary Statistics of Key Variables

Variable	Count	Mean	Std_Dev	Min	Max
denial_rate	29792	0.22	0.07	0.00	1.00000e+00
loan_amount_000s	29792	134.42	69.67	5.00	3.55056e+03
applicants_000s	29792	81.30	29.12	15.50	1.13650e+03
total_loans	29792	5133.21	17328.98	1.00	7.80256e+05
num_failed_loans	29792	0.02	0.17	0.00	1.00000e+01
Federal_Interest_Rate	29792	0.01	0.01	0.00	5.00000e-02
Unemployment	29792	0.07	0.03	0.01	2.90000e-01
minority_pct	29792	13.93	15.39	0.31	9.17300e+01
MedianHousePrice	35116	45938.63	12097.82	17488.00	1.36191e+05

*Table 1 (*Source FDIC Bank Failures Data, HMDA Mortgage Data, and US Census Data 2007–2017)*

Table 2 shows the breakdown of denial rates across counties with failed banks, grouped by quartiles of total failed assets. The mean denial rates are fairly similar across the quartiles, ranging from 0.170 to 0.185, with standard deviations between 0.046 and 0.065. This suggests that, at the basic level, on average, exposure to larger bank failures is not associated with substantially higher average denial rates than exposure to smaller failures.

At the same time, the minimum and maximum denial rates vary widely within each quartile, highlighting considerable heterogeneity across counties. This dispersion suggests that mortgage outcomes are influenced by a range of factors beyond the size of failed banks. Overall, the initial descriptive statistics suggest that any relationship between bank failure severity and denial rates is not immediately apparent in the raw, averaged data. In total, the sample includes 366 failed banks across the United States.

Denial Rates by Total Failed Assets Quartiles

Quantile.of.Total.Failed.Assets	Mean	Standard.Deviation	Minimum.Value	Maximum.Value
0-25%	0.185	0.065	0.082	0.482
25-50%	0.174	0.053	0.098	0.380
50-75%	0.170	0.050	0.083	0.334
75-100%	0.171	0.046	0.075	0.282
Total	0.175	0.054	0.075	0.482

*Table 2 *(HMDA and FDIC, 2007–2017)*

Figure 2 displays a scatter plot of the number of failed banks (x-axis) and the mortgage denial rate (y-axis) at the county-year level. Each point represents one county-year observation. As shown in Figure 2, there appears to be at first glance no real relationship between a failed bank and a county's annual denial rate. This initial visual suggests that any relationship between bank failures and mortgage denial may be subtle or confounded by other factors.

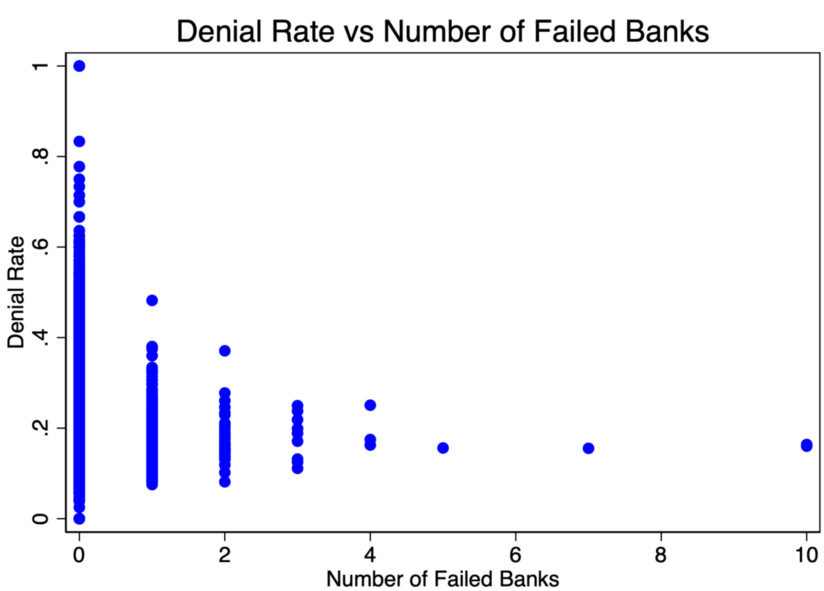

*Figure 2 *(Author Creation Using Data Set)*

6. Results

The model is estimated using a fixed-effects panel regression with standard errors clustered at the county level. Table 3 presents the main results. In the baseline specification, which includes only fixed effects, one additional failed bank in the previous year is associated with a 0.15-percentage-point increase in the denial rate. This estimate is statistically significant at the 5% level and is consistent with the theoretical prediction that a bank failure restricts local credit supply. However, once macroeconomic variables are added, the magnitude of the coefficient declines to 0.11 percentage points and loses statistical significance. When demographic and county-level economic controls are included in the full specification, the estimated effect becomes close to zero and remains insignificant. These results suggest that the initial positive relationship is explained by broader economic conditions correlated with both bank failures and mortgage outcomes. In other words, counties experiencing financial distress may see both bank failures and higher denial rates, but the failures themselves do not appear to exert a large independent effect once those conditions are controlled for.

Table 3: Effect of Bank Failures on Mortgage Denial Rates

Variable	**Baseline (1)**	**Macro Controls (2)**	**Full Controls (3)**
lag_fail	0.00147** (0.000708)	0.00111 (0.000692)	0.000385 (0.000669)
Federal_Funds_IR	6.987*** (0.144)	5.890*** (0.213)	
Unemployment_Rate	0.112*** (0.0306)	0.138*** (0.0299)	
ln_income			-0.0307*** (0.00670)
ln_loan_amt			-0.00812** (0.00356)
minority_pct			-0.00233*** (0.000745)
ln_pop			-0.0332** (0.0137)
ln_median_inc			-0.00868 (0.00809)
Observations	26,995	26,995	26,995

Notes: Standard errors in parentheses, clustered at the county level. County and year fixed effects included. Significance: $p<0.10$, *$p<0.05$, **$p<0.01$.

Figure 3 presents an event-study of mortgage denial rates surrounding bank failures. The coefficients for the years before and after a failure are small and unreliably estimated, with confidence intervals that include zero throughout the window. This pattern indicates no clear break in denial-rate trends at the time of failure, supporting the parallel trends assumption. This supports the difference-in-differences design and reinforces the finding that bank failures have only limited effects on mortgage denial rates.

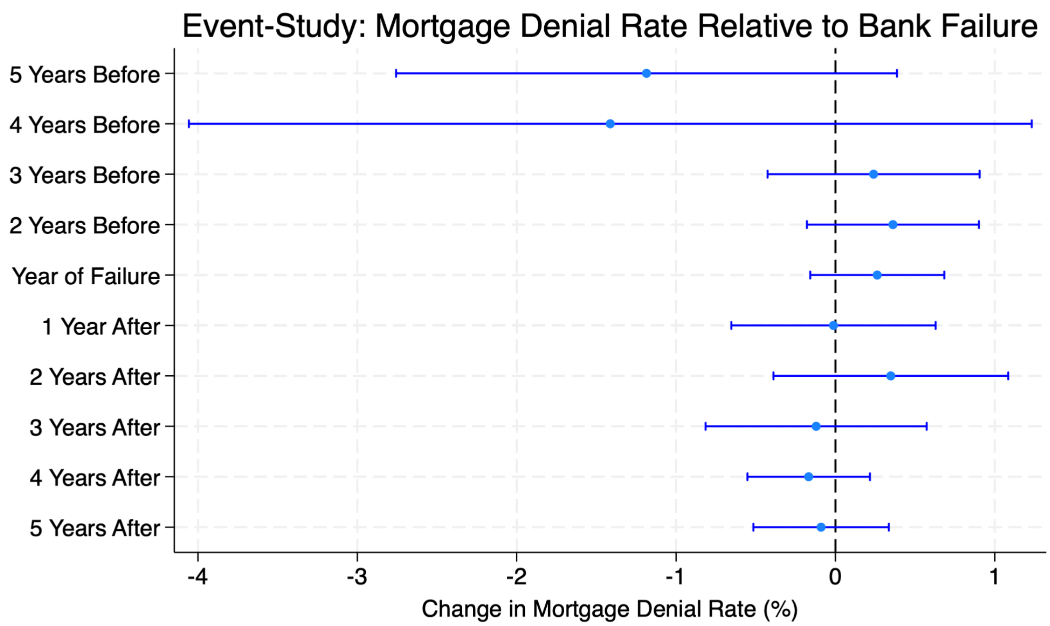

*Figure 3 *Event-study estimates of mortgage denial rates relative to bank failure. Each point represents the change in denial rate (%) in a given year relative to the year of bank failure, with 95% confidence intervals. Coefficients are estimated using county and year fixed-effects regressions with clustered standard errors.*

The control variables align with expectations. Higher applicant income and larger loan amounts are associated with lower denial rates, reflecting stronger borrower profiles. Conversely, higher unemployment and a larger minority population share are associated with higher denial rates, consistent with more challenging economic conditions and tighter lending environments. Median income and population size also display effects that reflect broader local economic health. These patterns reinforce the importance of local economic structure in shaping access to mortgage credit.

To assess the stability of the results, Table 4 presents three robustness checks. First, the study restricts the sample to counties that experienced at least one bank failure in any year, ensuring that the estimated effect is not driven by the large number of counties with no failures. Because the independent variable is lagged, the model captures how failures in the previous year affect the current-year mortgage denial rate. Even with this restriction, the coefficient on lagged failures remains small and statistically insignificant.The second robustness test involved excluding the years 2008–2010, removing the period most affected by the financial crisis. Because the crisis involved both widespread bank failures and a hit to mortgage markets, excluding it provides a more conservative test. The estimated effect again remains small and insignificant, indicating that the main results are not driven by dynamics involving a crisis. The third analysis replaces the count of failed banks with the total assets of failed banks, helping to better capture the magnitude rather than just the number of failures. In this specification, failed assets have a positive and statistically significant effect on denial rates, suggesting that larger failures may generate noticeable disruptions, even if the simple count of failures does not. This result makes intuitive sense, where the collapse of a large institution removes more credit supply and disrupts more existing relationships than the failure of a small one. Across all three models, the control variables continue to behave consistently with the theory proposed. Moreover, the robustness checks collectively indicate that the core findings are stable across alternative specifications.

Table 4: Robustness Checks – Mortgage Denial Rates

Variable	**Counties w/ Bank Failure (1)**	**Excluding 2008-2010 (2)**	**Alt: Failed Assets (3)**
lag_fail	0.000992 (0.000774)	0.000891 (0.000933)	–
ln_income	-0.0341 (0.0266)	-0.0225*** (0.00771)	-0.0481** (0.0242)
ln_loan_amt	0.0107 (0.0381)	-0.00963*** (0.00315)	0.0204 (0.0369)
minority_pct	0.00169 (0.00376)	0.00598*** (0.00108)	0.00118 (0.00375)
ln_pop	-0.0851 (0.117)	-0.109*** (0.0197)	-0.155 (0.118)
ln_median_inc	-0.0878* (0.0496)	0.0331*** (0.00999)	-0.0392 (0.0630)
Unemployment_Rate	-0.0332 (0.198)	-0.0643** (0.0317)	-0.186 (0.191)
Fed_Funds_IR_Annual_Avg	4.495*** (0.479)	-2.592*** (0.126)	2.466*** (0.405)
failed_assets_bil	–	–	0.0377*** (0.00765)
Observations	363	18824	366

Notes: Standard errors in parentheses, clustered at the county level. County and year fixed effects included in all models. Significance: *p<0.10, **p<0.05, ***p<0.01

Taken together, the results suggest that while bank failures may generate short-run disruptions to mortgage supply, their independent effect on county-level mortgage denial rates is limited once broader economic and demographic factors are taken into account. Local economic conditions—income, unemployment, and demographic composition—appear to play a far more central role in determining mortgage approval outcomes than the occurrence of bank failures themselves. The robustness checks further strengthen this conclusion, demonstrating that the findings are not sensitive to sample restrictions, crisis years, or alternative measures of failure severity.

7. Conclusion

This study examined whether local bank failures affect household access to mortgage credit, using county-level data from 2007 to 2017. By combining FDIC bank failure records with HMDA mortgage data and employing a difference-in-differences approach, I tested whether counties exposed to failed banks experienced higher mortgage denial rates. The results indicate that once broader economic and demographic conditions are accounted for, the independent effect of bank failures on denial rates is limited or undetectable. While larger failures, measured by total assets, can create noticeable disruptions, smaller failures appear to have minimal direct impact. Overall, local economic conditions—such as income, unemployment, and population composition—play a more central role in shaping mortgage outcomes than the closure of individual banks.

Several limitations of the study should be addressed. First, the analysis is conducted at the county level, which may hide more localized effects of bank failures. The true impact of a bank failure may be concentrated in certain towns or neighborhoods, but these effects are averaged out when using county-level data. Second, the difference-and-differences approach relies on the assumption that, without a bank failure, treated counties would have followed similar trends as control counties. While the model controls for many factors, there is no way to directly test this assumption. Third, the study focuses only on mortgage denial rates. Bank failures may also affect loan terms, interest rates, or how long it takes for a loan to be approved, which are not captured here. In addition, the analysis does not fully account for how nonbank lenders and fintech firms respond to bank failures. These lenders may step in quickly and replace lost credit, reducing the observed effect of failures.

Future research could use more detailed geographic data and examine other measures of credit access or credit risk. Studying how alternative lenders respond to bank failures and whether repeated failures have longer-term effects on housing markets would also help highlight our understanding of these dynamics.

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