Acquiring Failed Banks*

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Abstract

Banks create value by issuing deposits and making loans, yet little is known about the relative importance of these two functions. I study this question in the setting of failed bank auctions. This allows me to obtain causal estimates by comparing outcomes for the winning bank to those of the second highest bidder. Consistent with a positive value effect from the acquisition, the winning bank experiences a large positive abnormal return upon announcement of the auction result. I show that this increased value is mainly due to deposits, not loans. After the acquisition, the winning bank sharply cuts lending to the failed bank's borrowers, including those who were not responsible for the bank's failure. However, the winning bank retains almost all of the failed bank's deposits, despite shutting down some of its branches. It does not channel these deposits into lending in other areas, indicating that the value of deposits is separate from their role in financing loans. Rather, it lowers deposit rates throughout its network, reflecting increased deposit market power. Overall, my results show that the deposit franchise is the main source of value in these acquisitions, and hence likely a principal source of bank value more broadly.

Keywords: Bank failure; acquisitions; bank regulation; competition

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[Latest version here]

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1 Introduction

Substantial empirical research supports the notion that banks have a special role in the economy[1]. But what makes banks unique? Is it the production of safe, liquid deposits (e.g., Gorton and Pennacchi (1990)) or information production through the screening and monitoring of loans (e.g., Diamond (1984))? Which side of the balance sheet does bank value primarily come from? Despite the importance of this question for our understanding of the business of banking, there is little empirical evidence establishing the relative importance of the aforementioned channels.

In this paper, I ask what determines bank value creation in a specific setting – the acquisition of distressed banks by healthy banks? Do acquirers make the purchase for lending opportunities or the deposit franchise? Features of the failed bank resolution process make it a compelling setting to answer this question. For all federally insured banks and thrifts in the US, the Federal Deposit Insurance Corporation (FDIC) has authority to administer the resolution of a distressed bank under a non-judicial process. For the spate of bank failures during the Great Recession and its aftermath (Figure 1), the FDIC primarily relied on competitive auctions to sell failing banks to healthy ones. I causally identify the impact of the auction by comparing outcomes for the bank that wins the auction to the bank that came second.

This setting allows me to surmount the primary challenge in identifying the effects of any kind of merger or acquisition. Banks that are interested in bidding for a particular failed bank might differ in other ways from a randomly selected bank. This selection effect confounds the econometrician's ability to identify the effect due to the acquisition itself. For instance, during the Great Recession, prior research has found that acquiring banks were more likely to be proximate, both in terms of geography and business model, to the failed bank (Granja, Matvos and Seru, 2017). The key to overcoming the identification challenge

[1] For instance, Reinhart and Rogoff (2009) show over eight centuries of data that financial crises are associated with longer recessions

is to find a reasonable counterfactual i.e. a bank or banks that can serve as a control group. I identify the bank that ended as the runner-up in each competitive auction and use it as the control group. The runner-up bank was also eligible to and interested in bidding for the failed bank, and as such is a plausible control. The identifying assumption in my standard difference-in-differences (DID) research design is that the treated and control banks were evolving similarly before the auction ("treatment"), and would have done the same in the absence of the treatment. I show that the winning and runner-up bank have similar observables, no standard characteristics predict which bank among the two would win the auction and the bids are close in value. These tests increase confidence in the plausibility of the identifying assumption.

Applying this empirical framework to the data, I find that acquiring a failed bank creates immediate value for the acquirer. For successful banks with traded equity, the average positive abnormal return is about 1.7% on announcement. This implies that even in a competitive auction process, there is wealth transfer from the FDIC to the acquiring bank. My next step is try to determine the source of this value addition. Do healthy banks acquire distressed ones for the access they receive to their lending opportunities ("asset-side view") or because of the deposit franchise they acquire ("liability-side view")? My results indicate it is the latter. Local lending collapses in markets in which the failed bank was present. For both residential mortgages and small business lending, originations decline about 50-80% from the level at which the failed bank was operating prior to being acquired. This result holds whether I use all banks or just the runner-up bank as the control group. On the other hand, the impact on deposits is muted. The decline in net deposit flows after acquisition is about 20% in the year following acquisition, and indistinguishable from zero thereafter. Additionally, the deposit rates that the winning bank charges after acquiring the failed bank are lower.

Why does lending decline when the failed bank is acquired by a healthy bank? One possibility is that the acquiring bank is using the acquired deposits to fund higher NPV loans in unaffected markets[2]. If the acquirer was financially constrained, access to a new source of deposits could facilitate increased lending in other markets (Gilje, Loutskina and Strahan, 2016). I do *not* find evidence supporting this hypothesis. Compared to the runner-up bank, the winning bank's lending in unaffected markets does not increase. However, I again find an impact on deposit provision. The acquiring bank is able to reduce deposit rates in these unaffected markets, reflecting its increased deposit market power.

Can the lending contraction simply be explained by the fact that these were bad banks making bad loans, and once a good bank took over it shut down the lending? Evidence seems to suggest that this is not the explanation. First, the result is not driven by local economic conditions since I carry out the tests at the bank-county-year level and am able to control for local economic shocks with county-year fixed effects. Additionally, the fact that small business lending also declines precipitously suggests that the result cannot be explained just by the fact that banks with bad lending technologies are being acquired. Most of the banks in the sample failed due to their exposure to commercial real estate (Cole and White, 2012). However, this remains an important concern in this setting which I further ameliorate with the next test.

My empirical strategy allows me to further tease out the mechanism leading to the lending decline by comparing markets that, as a result of the acquisition, see consolidation and those that don't. Prior to failure, in some of the failed bank's markets the winning bidder is present but not the runner-up while in others the runner-up is present but not the winner. Based on the auction results, the former market sees consolidation while the latter doesn't. Treating the failed bank and the bidder in each of these markets as a combined entity, I test what happens to lending in these two types of markets after acquisition. I find that small business lending reduces significantly more in the market undergoing consolidation. On the other hand, the decline in deposit flows in both kinds of markets is similar. Why does consolidation hurt lending but not deposit flows. The answer may lie in how acquiring

[2]Unaffected markets are those in which the failed bank was not operating

banks operationalize consolidation. I show that a branch previously belonging to the failed bank is much more likely to be shut down post acquisition if the acquiring bank already had a branch in the same market. Given that small business lending is considered to be information intensive (Petersen and Rajan, 1994; Berger and Udell, 1995), branch liquidation can have strong effects through the destruction of relationship-specific capital. The differential effect in the lending decline between markets with and without consolidation also reduces the concern that the lending decline is purely driven by bad loans not being originated. If that was the case, there should be no difference between the two markets since they only differ in the presence of the winner or runner-up and not in terms of the failed bank itself. A surprising aspect of these results is that consolidation, and hence branch closure, does *not* seem to impact deposit retention. This further supports the conjecture that deposits is what drives the acquisition. The argument can be made in a revealed preference sense – if deposits are what the acquirer cares about and failed bank branch closure does not affect the ability to retain deposits, then closing the branch is optimal[3]. The overall weight of evidence is consistent with the deposit franchise being seamlessly transferred through the auction process but the loan production technology being destroyed.

This paper contributes to a number of strands in the banking and corporate finance literature. First, it adds to analyses of the resolution of failed banks. Much of the prior literature on this topic focuses on the savings and loan (S&L) crisis of the 1980s. The classic study on failed bank auctions during the 1970s-1980s, James and Wier (1987), finds significant positive abnormal returns for the winning bidder in a sample of 19 auctions. Importantly, the statutory environment under which those auctions took place was different since the 'least cost resolution' language was explicitly introduced by the FDICIA of 1991. While James (1991) documents that the losses suffered during the S&L crisis average about 30% of failed bank assets, Giliberto and Varaiya (1989) shows that winning bids were higher for more competitive auctions implying lower losses for the FDIC. I confirm that even during

[3]Operating a branch comes with costs of employees, rent etc.

the Great Recession, the auction process leads to positive gains for the successful bidder, implying wealth transfers from the FDIC to the winner. I also show that more competitive auctions, proxied by number of bidders, lead to lower losses for the FDIC.

It is perhaps unsurprising that the magnitude of losses during the Great Recession and its aftermath were similar to those during the S&L crisis. Cole and White (2012) show that the observable determinants of bank failures during both eras were the same, namely the elements of the CAMELS rating system as well as exposure to commercial real estate. They do *not* find that residential MBS exposure mattered significantly. Balla, Prescott and Walter (2015) conclude that the reforms of the early 1990s did not matter much in terms of realized losses on failed banks but might have reduced the number of banks that went bankrupt. Cole and White (2017) suggest that regulatory forbearance was a factor in the magnitude of realized losses. Failing banks should have been resolved earlier than they were according to their model. Theoretical models looking at the optimal policy for closing failing banks include Acharya and Yorulmazer (2007), Bolton and Oehmke (2016) and Colliard and Gromb (2017) among others.

Perhaps the study closest to mine in terms of the study of the resolution process is Granja, Matvos and Seru (2017). The authors ask the question of which healthy banks acquire failed banks i.e. they are interested in the *selection* question. They compare the winning bank with the universe of banks (and with the entire set of bidders) and find that distance to the failed bank, both physically and in terms of asset portfolios, is a significant predictor of who acquires the failed bank. They also document that limited capital available to potential acquirers might have limited the amounts they bid, increasing the cost borne by the FDIC. They do not distinguish between competitive and non-competitive auctions. My empirical strategy, instead, is based on controlling for the selection issue by comparing outcomes for winning and losing banks in competitive auctions. Additionally, I go beyond their analysis by looking at the lending and deposit market consequences of these acquisitions. They focus on the selling process; I focus on what comes after.

I also contribute to the old literature examining the effect of bank failures on economic activity. Bernanke (1983) argues that the raft of bank failures in the early 1930s played a significant role in the propagation of the Great Depression. The destruction of bank-specific information led to a squeeze in loan supply, leading to negative effects on economic activity. The key econometric challenge in identifying the effect of bank failure is distinguishing that shock from prevailing economic conditions. Ashcraft (2005) cleverly surmounts that challenge by analyzing a couple of unique cases during the S&L crisis when a couple of "healthy" bank subsidiaries were closed by the FDIC due to troubles at the bank holding company level. Though economic conditions were not responsible for the failure of these "healthy" banks, their closure was followed by reduced economic activity in their local markets. Kandrac (2014) studies the effects of bank failures during the Great Recession and its aftermath. The author matches counties affected by bank failures to unaffected counties based on observables and documents that the affected counties perform worse following bank failure. I show that there was a significant disruption in lending activity when failing banks were allocated to healthy ones.

More broadly, my analysis relates to the old question of what makes banks "special". There are three classes of theories. The liability-centric view holds that producing safe, liquid securities i.e. deposits is what makes banks unique (e.g., Gorton and Pennacchi (1990)). The asset-centric view is organized around information production through the screening and monitoring of loans (e.g., Diamond (1984)). The synergistic view highlights that banks have an advantage in producing liquidity on demand to *both* borrowers and depositors (e.g., Kashyap, Rajan and Stein (2002)). The relative importance of these functions is an empirical question. Egan, Lewellen and Sunderam (2017) construct a structural model of both sides of the bank's balance sheet in order to shed light on this question. They find that deposit productivity, a bank's expertise in producing deposits with a given set of inputs, contributes more to bank value in the cross-section than asset productivity, a bank's expertise in generating income from its loan portfolio. My results are complementary to theirs – in a more reduced-form framework, I show that at least distressed bank acquisitions are motivated by the prospect of acquiring access to the liabilities rather than the assets.

The number of commercial banks in the United States has reduced from almost 11000 at the time of the Reigle-Neal Act of 1994 to less than 5000 today[4]. This consolidation has led to renewed interest in the subject of bank mergers and acquisitions. Levine, Lin and Wang (2017) looks at a comprehensive sample of bank takeovers over the last 30 years and finds that an overlap in *geographic* networks is a significant determinant of two banks merging and is also associated with improved post-merger efficiency. Garmaise and Moskowitz (2006) studies the real and social effects of bank mergers. Berger et al. (1998) shows that small business lending is particularly hurt following bank mergers. Nguyen (2016) finds similar effects on local small business lending following a number of mega mergers during the 2000s, an outcome she credits to the closure of branches caused by consolidation. I also document that consolidation leads to branch closure and a decline in small business lending. However, an examination of the deposit side reveals a rationale for branch closure even though lending opportunities are lost – banks manage to retain deposits despite consolidation.

The rest of the paper is organized as follows: Section 2 describes the FDIC's bank resolution process, Section 3 details empirical methodology, I describe the data I use in Section 4 with basic results presented in Section 5 and the role of consolidation explored in Section 6. Section 7 concludes.

2 The Failed Bank Resolution Process

The insolvency of banks, unlike those of other corporates, is not covered under the provisions of the Federal Bankruptcy Code. Rather, for all federally insured banks and thrifts, the FDIC has authority to administer the bankruptcy under a non-judicial process[5]. The

[4] The Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 removed all remaining restrictions on interstate banking and competition. The time series of number of commercial banks is available at https://fred.stlouisfed.org/series/USNUM

[5] The FDIC provides a detailed account of its process in its Resolution Handbook available at https://www.fdic.gov/bank/historical/reshandbook/resolutions_handbook.pdf

financial condition of these depository institutions is constantly monitored by their federal or state banking regulators. The process to resolve a failing bank is initiated when its regulator believes the bank is insolvent or "critically undercapitalized" (defined as less than two percent of equity capital to assets)[6]. In most cases, the FDIC issues a notice to the bank to take "prompt corrective action", a final chance to raise capital privately. If the bank fails to do so or if its condition deteriorates in the interim, the regulator and the FDIC may decide to close the bank with the FDIC stepping in as receiver. No judicial recourse is available to the failed bank or its creditors to contest the seizure of the bank (Ragalevsky and Ricardi (2009)).

FDIC's Role

The FDIC acts in two distinct capacities: in its 'corporate' capacity, it provides deposit insurance to covered banks and performs as primary regulator for some of them; in its 'receiver' capacity, it is responsible for winding up the affairs of a failed bank. The FDIC has authority to take any action it believes is necessary to ensure the 'least cost resolution' of the bank[7]. Before being formally named receiver, the FDIC undertakes a valuation of the bank's assets and liabilities. It then evaluates options for resolution, invites bids if necessary and then determines the final resolution strategy to ensure least cost to the DIF. This entire process takes approximately 90 days (FDIC (2015)). During the Great Recession and its aftermath, the primary option relied on was the Purchase and Assumption (P&A) transaction. In such a transaction a healthy bank would *purchase* the assets and *assume* the deposits of the distressed entity (Bennett and Unal (2015)). P&As are of multiple types with the most common being whole bank and loss sharing P&As. In the former, essentially all the assets are purchased by the acquirer, usually at a substantial discount. Under loss-share agreements the FDIC agrees to share in subsequent losses on specific pools of assets. These

[6]Even if these conditions are not met, regulators have significant leeway in taking action (Ragalevsky and Ricardi (2009))

[7]This requirement is mandated by the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA)

agreements were used widely during the recent spate of failures in order to keep assets in the private sector (Kandrac, 2014).

Bidding Process

The acquiring bank is identified through a competitive bidding process. The auction under the P&A process is a first-price sealed bid auction. The FDIC invites eligible bidders to participate in the process, and to conduct due diligence on the failed bank. Only other financial institutions or private investors in the process of obtaining a bank charter are eligible to bid on a failing bank prior to closure. Bidders must have a CAMELS[8] composite and management component rating of 1 or 2 and satisfactory Community Reinvestment Act and anti money laundering records. The identity of eligible bidders is not revealed. Interested bidders, among those invited, are then given access to financial information on the failing bank. This part of the process is confidential on both sides. About 10 days before the closing date, the bidders submit one or more bids. Most bids have at least two components: an 'asset discount' on the market value of the bank's assets and a 'deposit premium' on the bank's deposit liabilities. Additionally, bidders can specify if they would like existing assets to be covered by loss sharing. Once all the bids are received, they are evaluated using the FDIC's proprietary models to determine the 'least-cost' bid. If no bids are above the liquidation value of the bank as determined by the model, the FDIC liquidates the assets. If there is at least one bid above the liquidation value, the bidder with the highest bid gets to acquire the failing bank. The announcement of failure and transfer to the winning bidder is always made on a Friday evening so as to allow minimum disruption to the bank's customers.

3 Empirical Strategy

The goal of this paper is to study the consequences of acquiring failed banks. I employ a difference-in-differences (DID) research design to accomplish the goal. The acquisition itself

[8]CAMELS, which stands for Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity to market risk, is a rating system developed by US bank regulators to monitor bank condition. Ratings are confidential.

is the treatment being investigated while the acquirer is the treated entity. However, the empirical challenge, as in all studies of mergers and acquisitions, is identifying an appropriate control group. Ideally, we want failed banks to be randomly assigned to banks i.e. to randomize the treatment. But acquirers choose which banks to target, and the factors that lead them to this selection might also influence outcomes in the post-treatment period. Under this plausible scenario, any measured treatment effect is biased.

In the absence of an ideal experiment, I use the auction results of the FDIC's failed bank resolution process to identify a plausible control bank for each treated bank. The runner-up in the auction is the natural choice as control. Other papers to use a similar strategy are Greenstone, Hornbeck and Moretti (2010) and Skrastins (2017). Both the treated and control bank in my setting i.e. auction winner and loser were not only eligible to bid, they were interested in acquiring the distressed entity. In that way, restricting the control group to the runner-up goes a long way in mitigating the selection problem.

The identifying assumption is that, in the absence of the treatment, the treated bank ("winner") would have evolved like the control bank ("loser"). This is also known as the "parallel trends" assumption. Though not directly testable, I provide evidence in later sections that there is reason to believe that the assumption is satisfied: treated and control banks look similar on observables, bank characteristics do not predict treatment, the winner is not expected by the stock market and the actual bids filed are close in value.

Empirical Specification

I implement a standard difference-in-differences research design (Angrist and Pischke, 2009) with the winning banks being the "treated" group and the runner-up banks being the "control" group. I treat each bank failure as a separate "case" (Greenstone, Hornbeck and Moretti (2010), Skrastins (2017)) and compare outcomes for the winning bank against the losing bank within each case. Specifically, I estimate the following equation:

$$Y_{fbt} = \alpha_{fb} + \delta_t + \beta WIN_{fb} \times POST_t + \gamma X_{fbt} + \varepsilon_{fbt} \tag{1}$$

where the outcome variable is measured at the failure-bidder-time level; here f references a specific bank failure or case, b stands for a bidding bank, and t is the time at which the outcome is measured. WIN_{fb} is a dummy taking a value 1 for the winning bank, and 0 for the losing bank within a case. $POST_t$ is an indicator taking value 1 for the periods following the failure, and 0 otherwise. The coefficient β on the interaction of these two dummy variables, $WIN_{fb} \times POST_t$, is the DID estimate of the average treatment effect. X_{fbt} is a vector of time-varying control variables at the bank level. The specification also includes two sets of fixed effects. The time fixed effects (δ_t) control for time-varying aggregate shocks. The failure-bidder fixed effects ($\alpha_f b$) control for time-invariant bank-level factors *within* a case. Including these fixed effects ensures that the impact of acquisitions is identified from just variation within the two banks in a case. Standard errors are clustered at the level of treatment i.e. at the failure-bidder level.

The coefficient β in Equation 1 is the average treatment effect in the periods after bank failure. In order to study how the treatment effect evolves in each period following the acquisition, I also estimate a dynamic version of the DID specification (Autor, 2003):

$$Y_{fbt} = \alpha_{fb} + \delta_t + \sum_{\tau \neq -1} \beta_\tau (D^\tau_{ft} \times \mathrm{WIN}_{fb}) + \gamma X_{fbt} + \varepsilon_{fbt} \tag{2}$$

Here, D^τ_{ft} is a dummy variable that takes a value 1 if period t is τ periods after the failure of bank f. The coefficient of interest is β_τ, which measures the difference, conditional on controls, in outcome Y between treated and control banks τ periods after the failure. I choose τ to vary from -3 to +3 with $\tau = -1$ the omitted category. In addition to allowing an analysis of the dynamics of the treatment effect, the inclusion of dummies for periods prior to the treatment also allows a visual examination of the "parallel trends" assumption underpinning the DID research design.

4 Data and Summary Statistics

Data Sources

I put together multiple datasets to conduct the analysis in this paper. Almost all the data used is publicly available or from standard sources.

Failed Bank Resolution Data: The FDIC provides a wealth of public information on bank failures[9]. These include information on the acquiring institution, type of transaction, cost borne by FDIC etc. On November 12, 2009, the FDIC board decided to make public bid and bidder information for resolutions from May 2009 onwards. The stated purpose was the public interest in this information and an opportunity to show that the FDIC was accomplishing its Congressionally mandated objective to achieve the lowest cost resolution of failed banks[10]. The bid data specifies the winning bid and bidder and the runner-up bid (known as the "cover" bid in FDIC parlance) and bidder. Lower ranked bids and names of bidders are also provided but they cannot be linked to each other. Additionally, only those bids are made public that were above the liquidation value determined by the FDIC. I parse all bid data available on the FDIC website. Bidders are matched by name to the FDIC Institution Directory to get the FDIC certificate number, a unique identifier that can be linked to other datasets.

Bank Financial Data: Quarterly data on the financials of failed banks, bidders and other depository institutions comes from the SDI database maintained by the FDIC[11]. The SDI has income statement and balance sheet data on all US depository institutions. I prefer to use the SDI database over the similar Reports of Condition and Income (or "Call Reports") since the latter do not have data for thrifts before 2012. All results in the paper are robust to using the Call Reports instead of SDI.

[9] Data on individual bank failures can be accessed at https://www.fdic.gov/bank/individual/failed/banklist.html

[10] Details on the policy change can be found at https://www.fdic.gov/about/freedom/biddocs.html

[11] Available at https://www5.fdic.gov/sdi/main.asp

Branches and Deposits: Data on branches and deposits at the branch level comes from the FDIC SOD[12]. The SOD covers the universe of U.S. bank branches at an annual frequency, and data is as of June 30 each year. Information is available on the parent bank and location as well as the volume of deposits held at the branch. The FDIC certificate number is used to match this annual branch data to the quarterly bank data.

Local Lending Data: I use two regulatory datasets published by the Federal Financial Institutions Examination Council (FFIEC) to get information on local small business and mortgage lending. Under the CRA, all banks with assets greater than $1 billion are required to disclose annual data at the county level on the number and dollar volume of loans originated to businesses with gross annual revenues below $1 million. The HMDA requires financial institutions to publish application-level data on mortgage lending activity. Information includes loan size, application decision, type of mortgage loan as well as location in terms of census tract and county. I aggregate these data to the bank-county level to determine the amount and number of mortgage loans originated annually.

Deposit Rates: Data on retail deposit rates is from Ratewatch, which collects weekly branch-level deposit rates by product. The data cover 54% of all U.S. branches as of 2013 (Drechsler, Savov and Schnabl, 2017). I restrict analysis to branches which actively set their own rates, and aggregate the weekly data to quarterly frequency. The SOD's unique branch identifier can be used to link the dataset to the SOD, and consequently the other data.

Stock Returns: Stock return data comes from CRSP. Listed banks are linked to the banking datasets using the CRSP-FRB link available from the Federal Reserve Bank of New York[13]. The Federal Reserve's RSSD id is linked to the FDIC certificate number using the FDIC certificate number.

[12] Available at `https://www5.fdic.gov/sod`

[13] Available at `https://www.newyorkfed.org/research/banking_research/datasets.html`

Sample Selection

There were 523 bank failures in the United States between 2007 and 2016. I exclude the 4 bank failures in Puerto Rico as well as the acquisition of Washington Mutual by JP Morgan Chase since the FDIC undertook a special process given the size of the failing institution. Figure 1 shows the time series of the remaining 518 bank failures during the 10 year period as well as the volume of assets and deposits held by the failing banks. Further, I exclude the 26 banks without an acquirer ("payouts") and the 13 transactions in which only insured deposits were acquired ("PI"). Of the 480 remaining purchase and assumption ("PA") transactions, there is no bid data on 43 since they occurred before the FDIC decided to change its policy on publicizing auction information i.e. failures before May 2009. Of the remaining 437, there are 193 transactions where there was either only a single bidder or the identity of the runner-up is not available or I am unable to match the name of the winner or runner-up to the FDIC Institution Directory. The lack of match is generally a result of a bidder being a private investment group not holding a bank charter. This leaves 244 bank resolutions in which the winning and second placed bidder are distinct and identifiable. This is the primary sample on which the analysis is conducted. The first failure in this sample is of Citizen's National Bank on May 22, 2009 and the last one is of North Milwaukee State Bank on March 11, 2016. Table 1 provides summary statistics on the entire set of 518 banks that failed as well as the 244 with competitive auctions. There does not seem to be much observable difference in the entire set compared to the sample of banks I use[14]. Perhaps mechanically, the cost to the FDIC is significantly lower in the case of the competitive auction sample.

Bidders

The empirical strategy in this paper relies on the assumption that the second-placed bank in a competitive failed bank auction provides the appropriate control for the winning bank in

[14]It must be remembered that some of the banks in the excluded sample might have had competitive auctions but bid data is not available since they failed before May 2009.

the regression framework. Here, I provide some evidence that this assumption is reasonable. I start by comparing the two groups of banks on observables. As Table 2 shows, on virtually all metrics the two sets of banks are similar. The characteristics shown are the ones that Granja, Matvos and Seru (2017) find to be significant in predicting which banks, among the universe of banks, are likely to acquire distressed banks. They include balance sheet and geographic elements. The last three rows of the table also show that the auction outcomes are close. On average, the deposit premium bid from the winner and loser are the same while the winner's asset discount bid is about 2% lower than that of the loser which drives the difference in bid value. Given that the bidders are about 7 times larger than the failed bank, these differences in bids are not large in terms of the acquiring banks. Though the mean comparisons are illustrative, it is possible that though the winners and losers don't differ on average, in a given auction observable characteristics determine who wins. For instance, if the larger bank among the two wins in a large majority of cases, then size would do a good job of predicting the winner. I formalize this intuition by testing, through univariate regressions, if the bank having the higher value for a given characteristic is more likely to be the winner or loser. In a sample where the characteristics are randomly distributed, the point estimate should be about 0.5. Hence, the null hypothesis is that the bank with the higher value of a given characteristic would win about 50% of the auctions. Figure 3 shows the results. For not a single metric is the null hypothesis rejected at the 5% level, and in each case the point estimate is not very different from 0.5 in magnitude either.

5 Results

Stock Return Event Study

I start the analysis of the effect of acquiring failed banks by examining the immediate market reaction to acquisition announcement. Do equity markets react favorably to news of a failed bank acquisition? Since the FDIC announces the auction result only on a Friday evening after markets close, the setting is quite ideal for an event study analysis. The analysis is restricted only to winners and losers from my sample of auctions, and only those with publicly traded equity. I use the market model for my base event study results[15]. I include failed bank fixed effects so that the identification of the treatment effect comes purely from within a case. Table 3 shows the results for a number of estimation windows around the announcement date. The acquisition of a failed bank is value-creating for the acquirer, with an immediate average positive return of around 1.7% compared to the control group. Also, the market reaction manifests on the trading day following announcement, and is seemingly not anticipated in any way. Figure 4 illustrates this point further by plotting the evolution of the cumulative abnormal return (CAR) for the winner banks against the loser banks. The two lines are close to each other till the trading day following the announcement, at which time the winner's CAR becomes significantly positive.

Balance Sheet Effects

I next move on to the effects that acquiring a failed bank has on the acquirer's balance sheet. Results from the estimation of Equation 1 at a quarterly frequency for a number of balance sheet measures is shown in Table 4. In Panel A, the control group is composed of *all* banks other than the acquiring bank. In this table, and subsequent tables, I show the results treating the universe of banks as the control group in addition to the results with only the runner-up bank in the auction as the control group[16]. Panel B shows the results from restricting the sample to the top two bidders in each failed bank case. The immediate, or static effect, of the acquisition is mechanical. Since all the transactions I study are P&A transactions in which the acquiring bank purchased almost all of the assets and assumed all the deposits of the failed bank, we expect to see the size of the bank increase by about the size of the acquired bank. This is what the first column in Panel B of Table 4 shows. The coefficient of 0.167 implies that assets grow about 18.5% following acquisition. Given

[15]Results are robust to using factor models, and using a banking industry return instead of the market return

[16]Another possible control group is the set of all non-successful bidders, not just the runner-up. The results with this control group are qualitatively similar to those with just the runner-up included, and hence are not reported.

that the average acquirer is about 7 times larger than the bank being acquired, it shows that the empirical model used does a reasonable job of picking up the treatment effect. In fact, the much larger coefficient of 0.254 in Panel A (implying a 28.4% growth rate in assets) illustrates the pitfalls of not using an appropriate control in the empirical model. The difference between the two coefficients suggests that the acquiring bank, and the runner-up bank, had growth opportunities in the post-treatment period compared to the universe of banks, irrespective of whether they acquired the failed bank.

The deposit-to-assets ratio also increases post acquisition. This is again almost mechanical since the deposit ratios of failed banks is much higher than the deposit ratio of healthy banks since the former have essentially no equity. There is a reduction in the proportion of liquid assets held by the combined entity post merger. Perhaps surprisingly, the change in the tier 1 capital ratio is not significant though the magnitude is similar to the corresponding increase in the deposit ratio. I also plot the dynamics of some of the balance sheet effects by estimating the specification in Equation 2. Figure 6 plots the result when the outcome variable is log(assets) while Figure 7 plots it for the deposits ratio. While the increase in size persists in the quarters following treatment, it does seem that the treatment effect for the deposits ratio starts dissipating with time.

These figures also provide visual support for the importance and validity of the DID research design. For instance, looking at the DID estimates in Figure 6 for the specification in which the control group is the set of all banks, it is clear that even in the period before acquisition, the acquiring bank is on a different growth path; it is growing faster than other banks. Only when the control group is restricted to the runner-up bank do we find both treatment and control to be on parallel paths prior to treatment.

Local Lending

Now I turn to the main focus of my analysis – the local lending consequences of acquiring a failed bank. I utilize two datasets that allow me to study two different categories of loans:

(i) HMDA for residential mortgage lending, and (ii) CRA for small business lending. I look at both the dollar volume of new loans as well as the number. Since results are largely the same using both datasets, I focus on the small business lending results in the main analysis. The results for residential mortgage loans are reported in Appendix C.

In order to conduct the local market analysis, it is important to distinguish between the different kinds of pre-acquisition markets in which the lending is done. The three types are: (i) *Target Only* markets – those in which only the failed bank operated prior to treatment and the acquirer did not; (ii) *Target+Acquirer* markets – those in which both failed and acquiring bank operated prior to treatment; and (iii) *Acquirer Only* markets – those in which only the acquirer operated prior to treatment, and not the failed bank. Figure B.1 provides a graphical illustration of these markets and how they look before and after acquisition. In the second type of market, I combine the activity of the failed bank and acquiring bank prior to treatment i.e. act *as if* they were already one bank (Berger et al., 1998). The reason for doing this is that otherwise the only treatment effect I would pick up is the static aggregation effect.

Before implementing the regression analysis, I simply plot the average time series of lending by the failed bank and all other banks in event time around the failure. I restrict this analysis only to *Target Only* markets since here I do not pick up any aggregation effect with the winner[17]. Figure 8 indicates a sharp decline in lending for both small business and mortgage lending at the time of the acquisition, and this does not recover in the years to come. At least in this aggregate analysis, there is also no real evidence that the failed bank was lending significantly more in the period before failure.

Table 5 shows the results for small business lending at the bank level. Panel A has the log of loan volume as the dependent variable while Panel B has the log of the number of loans. These bank-level results are split by the kind of pre-acquisition market in which the lending is done.

[17] After failure, in *Target Only* markets the failed bank is simply replaced by the winning bank

The results in the two tables are stark and largely consistent. Lending in those markets in which the failed bank was operating in the year prior to its failure drop drastically post acquisition. In *Target Only* markets, the volume of small business lending falls by a staggering 75%. In *Target+Acquisition* markets, results are similar with a drop of 69% in small business lending. In Figure 9, I plot the dynamic version of these results. These results show that the drop in lending manifests in the year of failure and persists in the years that follow.

A concern with the above results is that they might reflect unobserved credit demand factors . After all, lending declines in *Target* markets might just be a reflection of the fact that failed banks belong to economically distressed regions. This concern is mitigated to some extent by the fact that I compare to the lending activity of the losing bank in the auction. However, to further emphasize that this effect is not driven by local demand factors, I repeat the local lending analysis at the bank-county-year level. Doing this allows me to include county-year fixed effects which absorb any local time-varying demand effects. I am also able to include bank-county effects, ensuring that within a case I am only identifying off the variation between the treated and control bank in the same county. In order to mitigate the effect of large changes in places with minor presence skewing the results, I restrict the analysis to counties in which the target or acquirer had substantial presence prior to the acquisition. I define substantial presence as having made at least 10 loans in the year prior to treatment. The results at the bank-county-year level are reported in Table 6. The results are largely consistent with those seen at the bank level. In target markets, the collapse in lending is staggering. Lending drops 81% in *Target Only* markets and 73% in *Target+Acquirer* markets. These bank-county-year level results suggest that lending drops are not much smaller in markets in which the acquirer was already present than markets in which it entered as a result of the acquisition. The results for *Acquirer Only* markets suggests that the drop in lending cannot be explained by a reallocation strategy whereby the acquirer uses the newly acquired deposits to fund more profitable loans in its incumbent markets.

Next, I ask whether other lenders step in to cover the shortfall caused by the acquired bank reducing its lending. Table 7 shows results from regressions at the county-year level. I relate aggregate small business lending at the county-year level to whether a failed bank was operating in the county in the year prior to its failure. Results indicate that following the bank's failure and acquisition, the aggregate number of small business loans in the county is about 1.2-1.9% lower than for unaffected counties. With the median failed bank having about a 2.3% share of lending in the county prior to failure, the magnitude of lending decline lines with that observed in the bank-level regressions. In fact directly regressing using the share of failed bank lending suggests about 40-50% of the failed bank's lending is lost.

Deposit Flows and Rates

The previous results indicate that failed bank acquisitions are not prompted by an interest in gaining access to the failing bank's lending markets. Are they instead prompted by interest in expanding the deposit network? In this section, I argue that the evidence suggests so. I use branch deposit data from the SOD at the bank-county-year level to test the extent to which acquiring banks maintain deposit presence post acquisition. Again, I combine the activity of the failed bank and acquiring bank prior to treatment i.e. act *as if* they were already one bank. Table 8 documents how deposit flows react post merger. In this case as well, there is a decline following the acquisition - deposit flows drop by about 19.5% (Panel A of Table 8). However, the magnitude of the decline is significantly smaller than that of the lending decline. Additionally, unlike the persistent reduction in lending seen in the previous sub-section, the dynamics of deposit flows shown in Figure 10 indicate that the outflows are transitory even though they are permanent. Consistent with the acquisition giving the acquirer increased deposit market power, results in Table 9 show that the acquirer is able to reduce deposit rates throughout its branch network. In particular, compared to the runner-up bank in *Acquirer Only* markets, deposit rates on 1 year CDs drop by about 0.09 percentage points

6 The Role of Consolidation

The results so far indicate that the lending of the failed bank declines when it is acquired by a healthy bank. Why is this happening? Heterogeneous effects across *Target+Acquirer* and *Target Only* markets are crucial in uncovering the mechanism. A potential hypothesis is that as the operations of the two entities are consolidated, relationship capital of the failed bank is lost (Nguyen, 2016). Under this hypothesis, lending should decline more in markets that see consolidation. Alternately, a hypothesis could be that the acquiring bank simply exits markets in which only the failed bank was operating as the acquiring bank possesses no information about the prospects in those markets. Under this hypothesis, more 'distant' markets are likely to see more disruption (Kandrac, 2014; Granja, Matvos and Seru, 2017). Here, lending would decline more in markets where the acquirer was not present prior to the acquisition.

My empirical strategy allows me to cleanly distinguish between these two hypotheses. Figure B.2 graphically illustrates the concept. In certain counties, prior to bank failure, the failed bank and winning bank are present while in others the failed bank and runner-up bank are present. Based solely on the outcome of the auction, the former kind of market is exposed to consolidation while the latter is not. I call the failed bank market with the winning bank present the 'treatment' market while the failed bank market with the runner-up bank is the 'control' market. If the auction had turned out in favor of the runner-up instead, the 'control' markets would have seen consolidation. Crucially, the failed bank was present in both markets. Variation comes only from how the geographic spread of the winner and runner-up interact with that of the failed bank.

A complication in identifying the effects of consolidation is that the failed bank is not observed in the data post acquisition. In the control markets, this is not a major issue since the failed bank is just replaced by the winning bank[18]. However, in the treated markets only

[18] The assumption here is that the winning bank would not have entered the market if not for the acquisition

the winning bank remain as shown in Figure B.2. To get around this issue, I take the sum of the failed bank and the winning bank (runner-up bank) in the treatment (control) markets both before and after acquisition. If the runner-up is a good control for the winner and the markets, then the sum of the failed bank and the winning bank in the treated market should be on parallel trends with the sum of the failed bank and the losing bank in the control market. The change following acquisition can be then be ascribed to the effects of the acquisition.

The results are presented in Table 10. Columns 1 and 2 show that the lending decline is stronger in markets exposed to consolidation compared to those in which the winning bank entered purely as a result of the acquisition. Columns 3 and 4 show the results from a similar specification but with deposit flows as the dependent variable. Perhaps surprisingly, there is no differential effect on deposit flows from the failed bank between these two kinds of markets. Also, columns 5 and 6 show that deposit rates are not significantly lower in consolidated markets. Figure 11 graphs the dynamic impact on small business lending and deposit flows for consolidated markets compared to unconsolidated markets.

7 Conclusion

The FDIC's bank resolution process is geared toward ensuring minimum disruption in banking operation. The regulator takes over a failing entity and attempts to get a healthy bank to take over all operations and assets. My results show that this process does succeed in minimizing disruption for depositors but is not able to ensure that borrowers who have come to rely on the failed bank are able to transfer their relationship to the acquiring bank. The welfare implications of this dynamic is something I do not attempt to quantify in this paper. This would depend on how well the affected borrowers are able to access service at other banks. In the presence of standard relationship frictions, the effect of the disruption is unlikely to be non-negative. By adding to the knowledge of existing policy, this paper also adds to the ongoing debate on how bank bankruptcies should be regulated.

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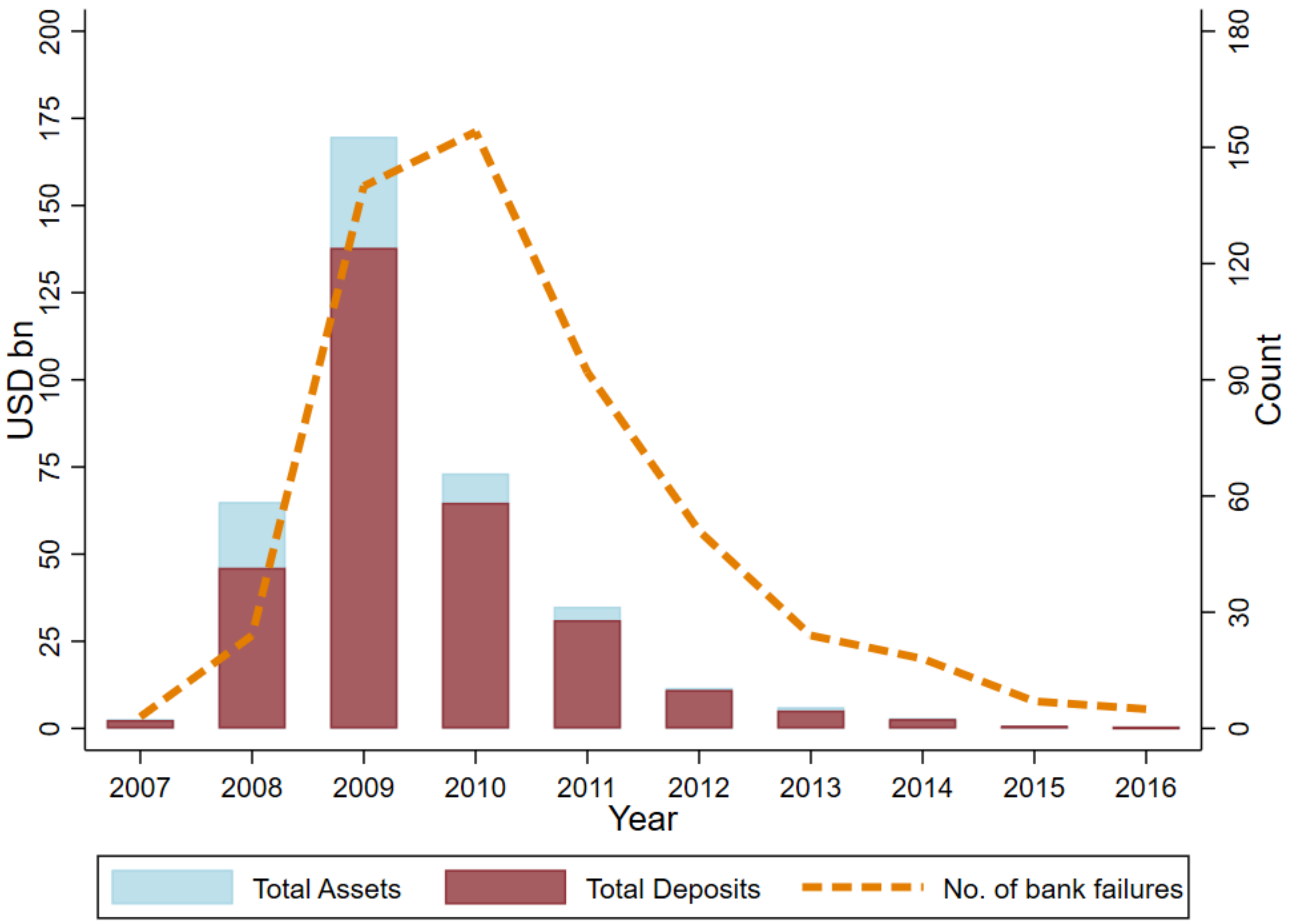


Figure 1: **Time series of bank failures**
The figure shows the number of banks that failed each year between 2007 and 2016, as well as the total assets and deposits on the balance sheets of the failed banks. *Data source: FDIC*

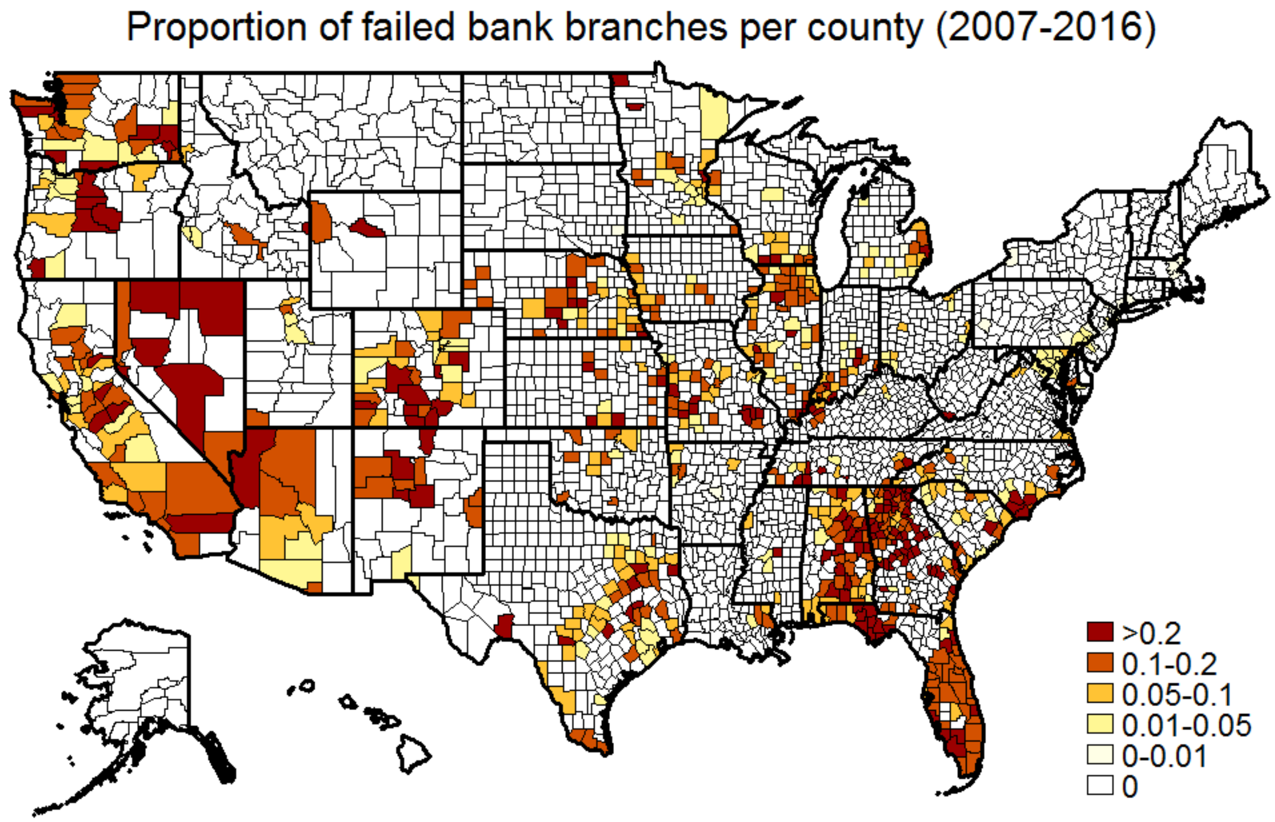


Figure 2: **Geographic Distribution of Bank Failures**
The map shows the county-level distribution of branches belonging to failed banks at the time of failure. It includes all banks headquartered in the 50 states that failed between 2007 and 2016. The number of branches belonging to failed banks is scaled by the number of bank branches in the county in 2006. *Data source: FDIC*

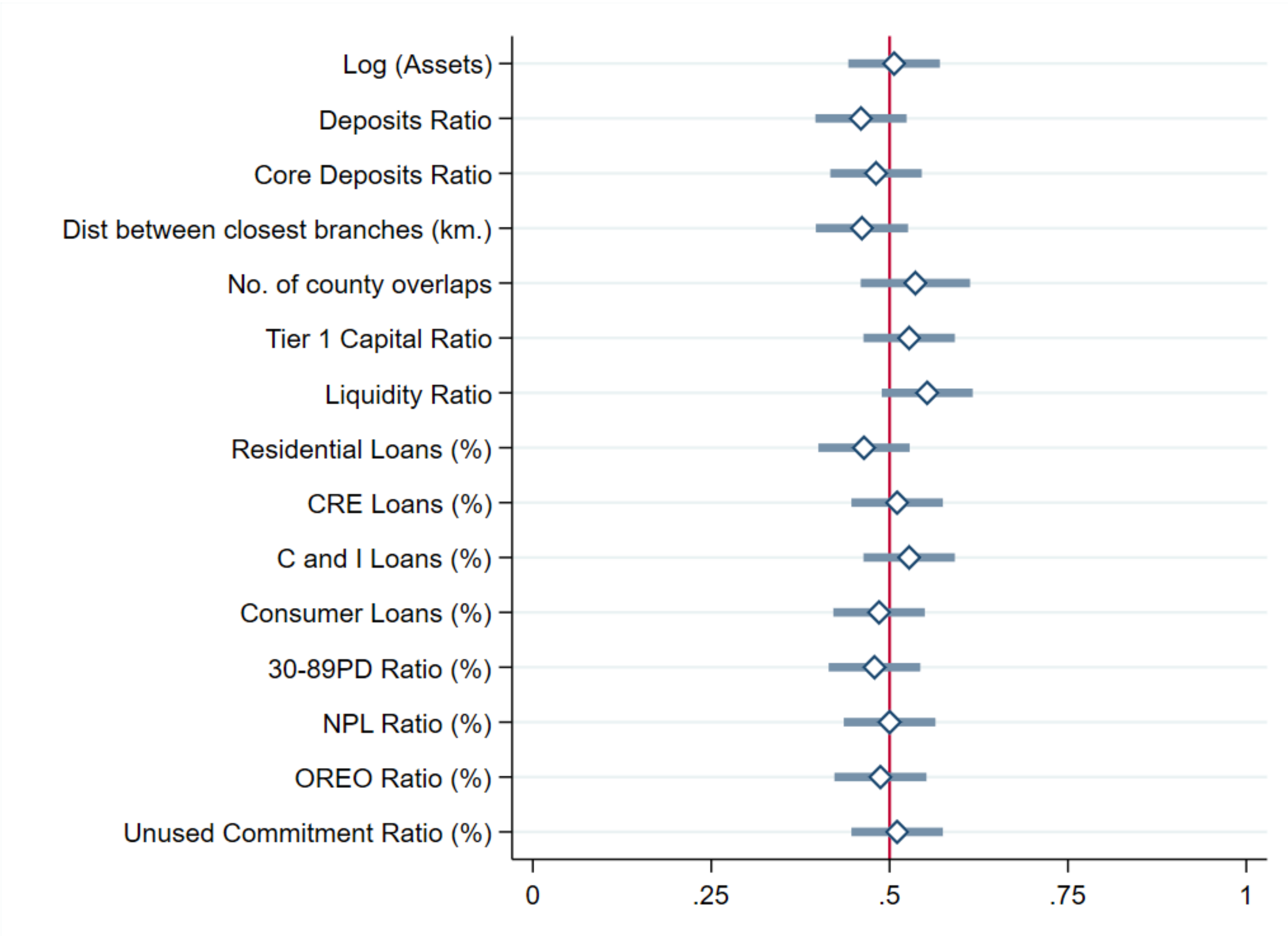


Figure 3: **Do Bidder Characteristics Explain Failed Bank Auction Outcomes?** For each bank characteristic on the y-axis, the figure plots the proportion of competitive bank auctions in which the bank with the higher value of the characteristic wins the auction. The comparison is done only between the winner and the loser. Confidence intervals at the 95% level are plotted. *Data source: FDIC, SDI*

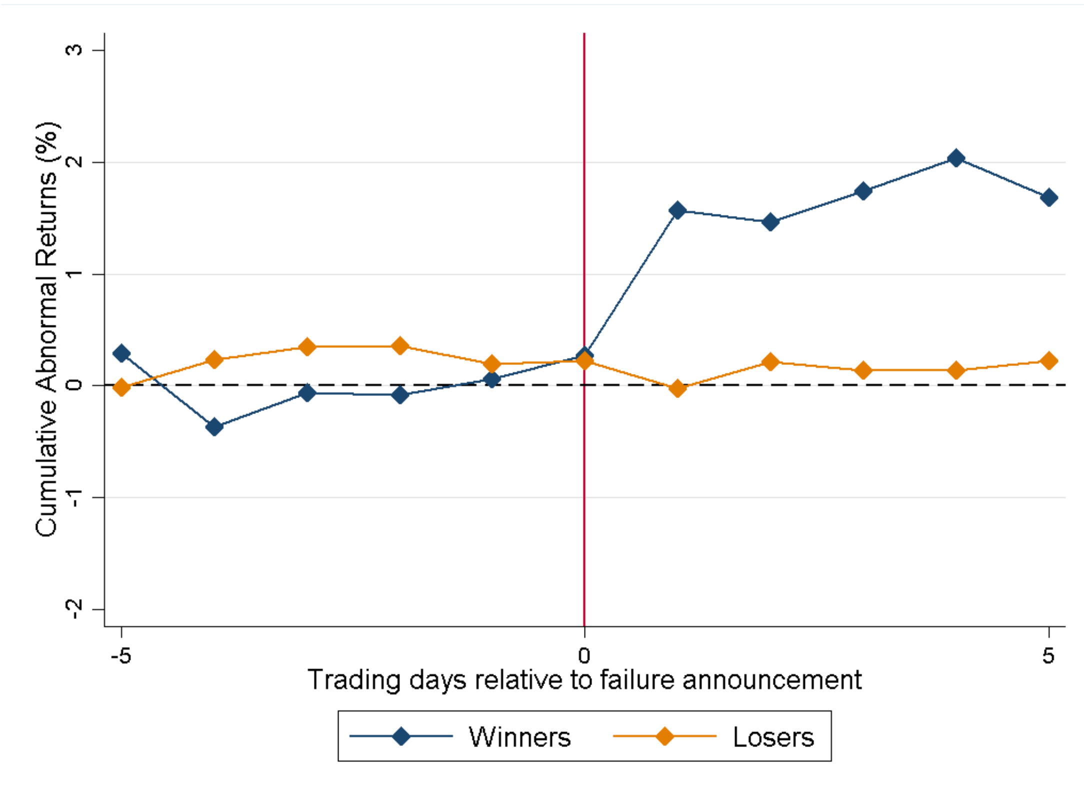


Figure 4: **CAR around announcement date**

The sample is restricted to bank failures in which the bidding was competitive, and consists of failed bank bidders for whom stock return data is available. A market model is used for estimation with the value-weighted market return proxying for the market return. The estimation window is 200 trading days and ends 11 trading days before the announcement date. The figure shows the distribution of CAR for winning bidders versus other bidders. The returns are in percentage points.

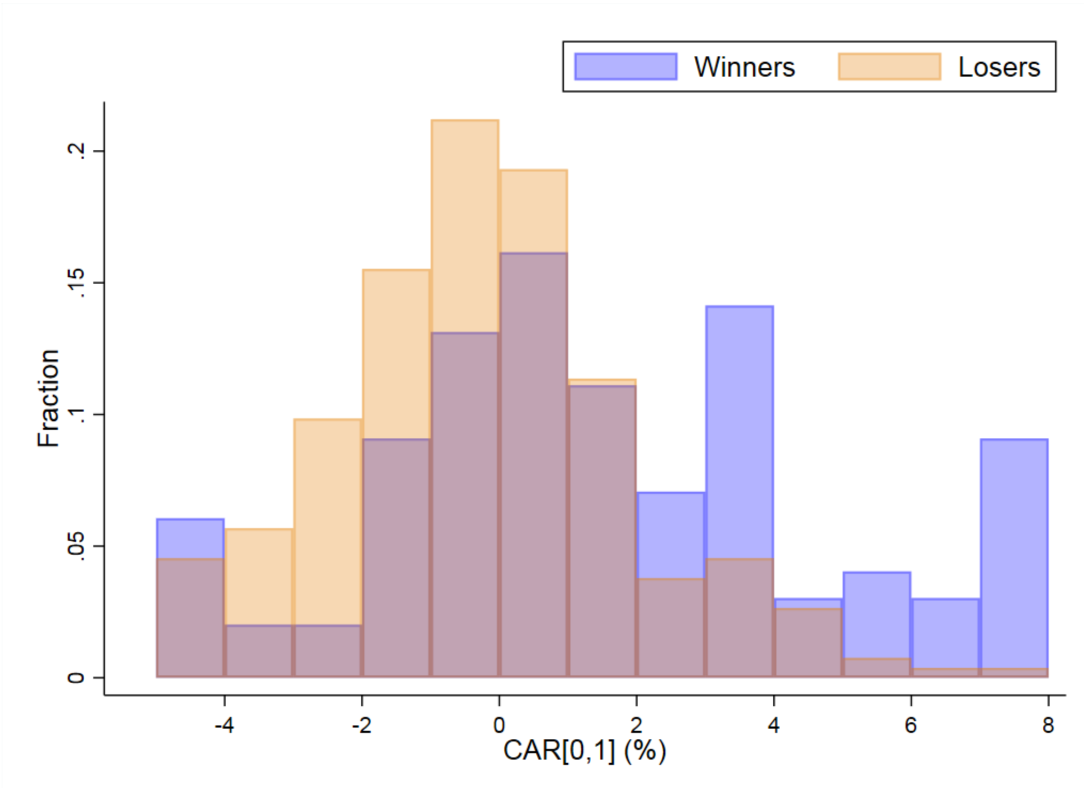


Figure 5: **Histograms of CARs around announcement date**
The sample is restricted to bank failures in which the bidding was competitive, and consists of failed bank bidders for whom stock return data is available. A market model is used for estimation with the value-weighted market return proxying for the market return. The estimation window is 200 trading days and ends 11 trading days before the announcement date. The figure shows the CAR for winners compared to other bidders. The returns are in percentage points.

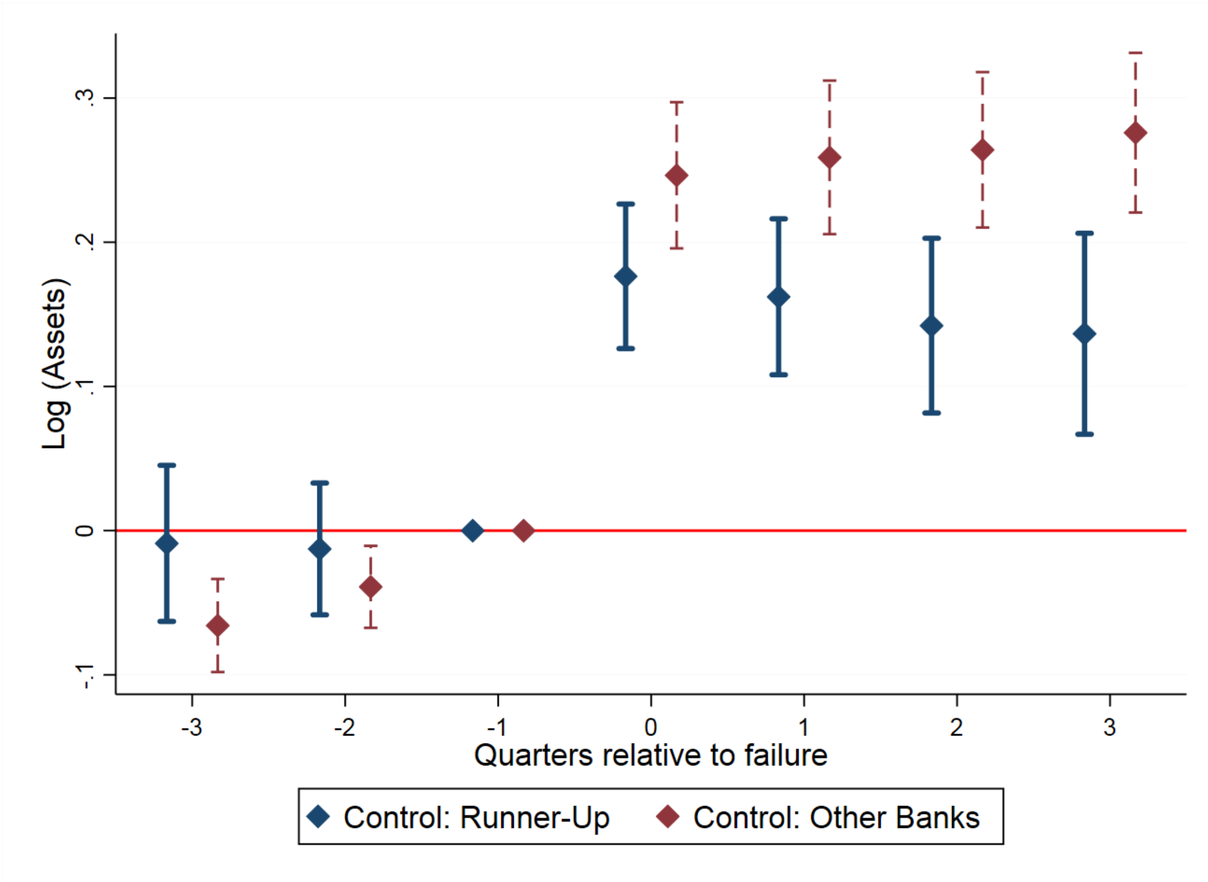


Figure 6: **Dynamics of Size of Acquirer**

The figure plots the coefficients from the following dynamic regression:

$$Y_{fbt} = \alpha_{fb} + \gamma_t + \sum_{\tau=-3}^{\tau=3} \delta_\tau (D_{bt}^\tau \times \text{WIN}_{bt}) + \varepsilon_{fbt}$$

The sample is restricted to bank failures in which the auction was competitive. The blue (maroon) markers represent estimates from regressions in which the control group is the runner-up (all other) banks. Failure-bidder and quarter fixed effects are included and clustering is at the failure-bidder level.

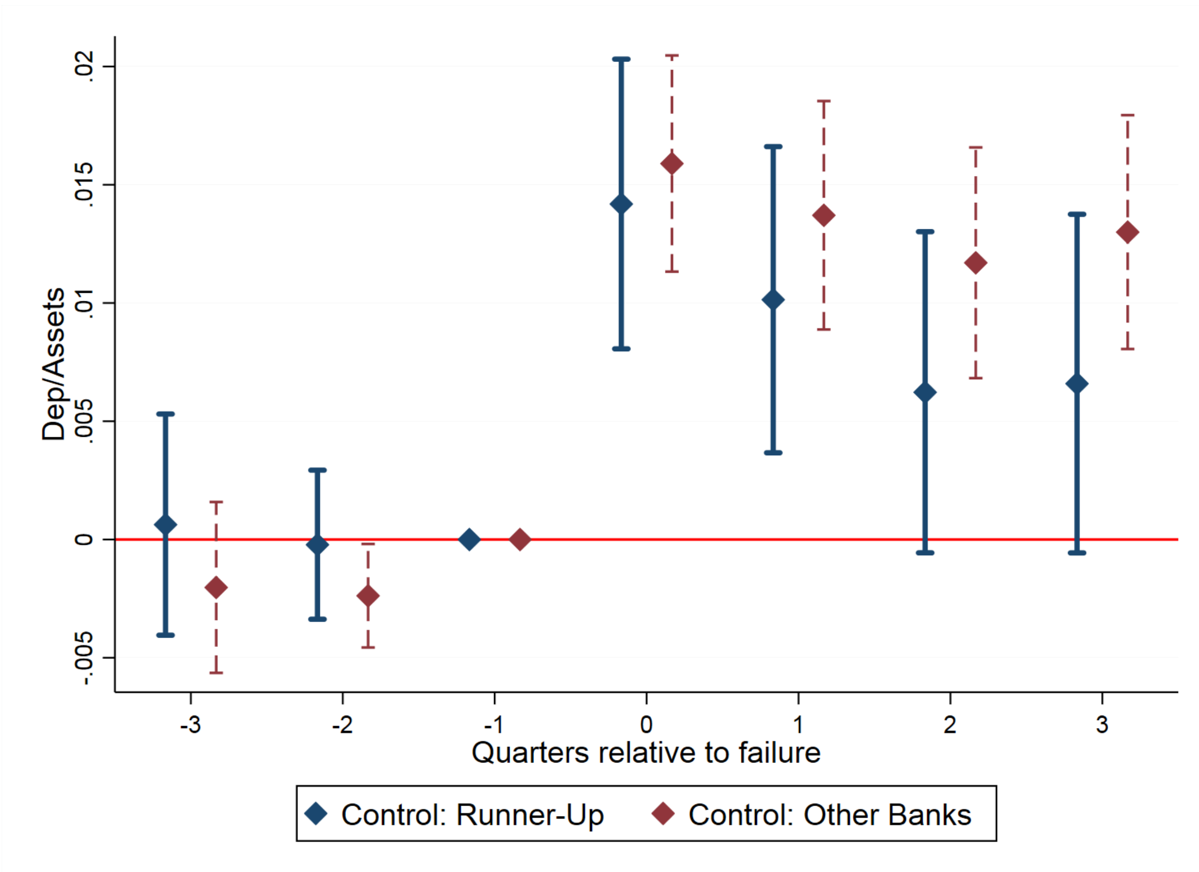


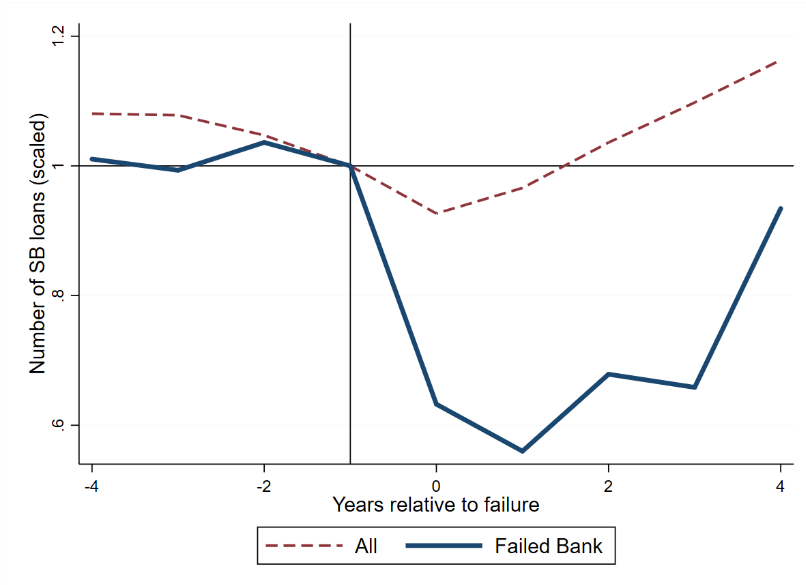
Figure 7: **Dynamics of Deposit Ratio of Acquirer**

The figure plots the coefficients from the following dynamic regression:

$$Y_{fbt} = \alpha_{fb} + \gamma_t + \sum_{\tau=-3}^{\tau=3} \delta_\tau (D^\tau_{bt} \times \mathrm{WIN}_{bt}) + \varepsilon_{fbt}$$

The sample is restricted to bank failures in which the auction was competitive. The blue (maroon) markers represent estimates from regressions in which the control group is the runner-up (all other) banks. Failure-bidder and quarter fixed effects are included and clustering is at the failure-bidder level.

(a) Small Business Lending



(b) Residential Mortgage Lending

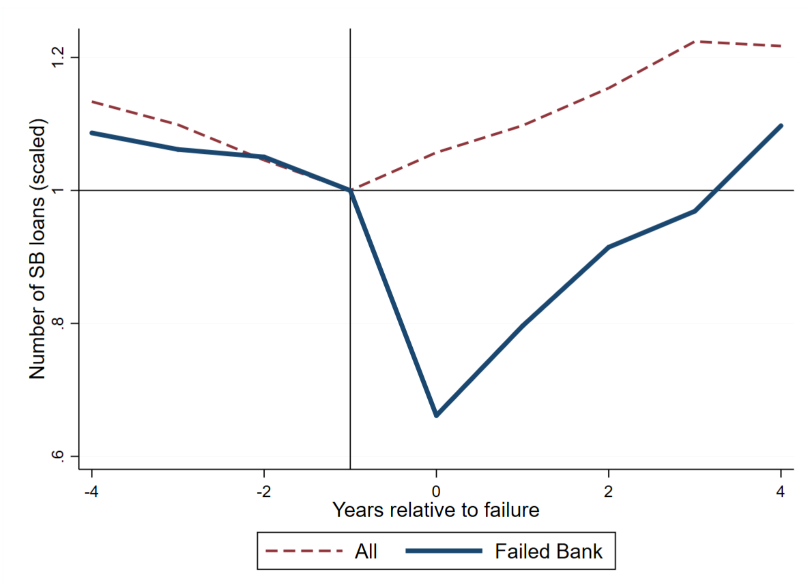
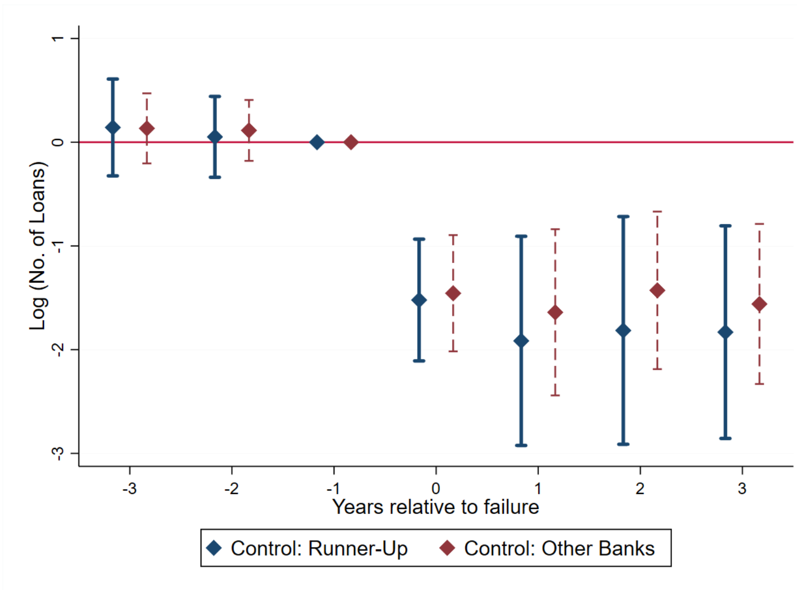


Figure 8: **Evolution of Failed Bank Lending before and after Acquisition**
The figure compares the average number of loans made by a failed bank (solid blue line) to those made by all other banks (dashed maroon line) in the period around acquisition. Analysis is restricted to only those failed bank markets in which the acquiring bank was not present i.e. Target Only markets. Thus, in the years following acquisition the failed bank's lending is identified through that of the acquiring bank. The number of loans is normalized so that in the year prior to acquisition, the number of loans made is 1.

(a) Target Only



(b) Target+Acquirer

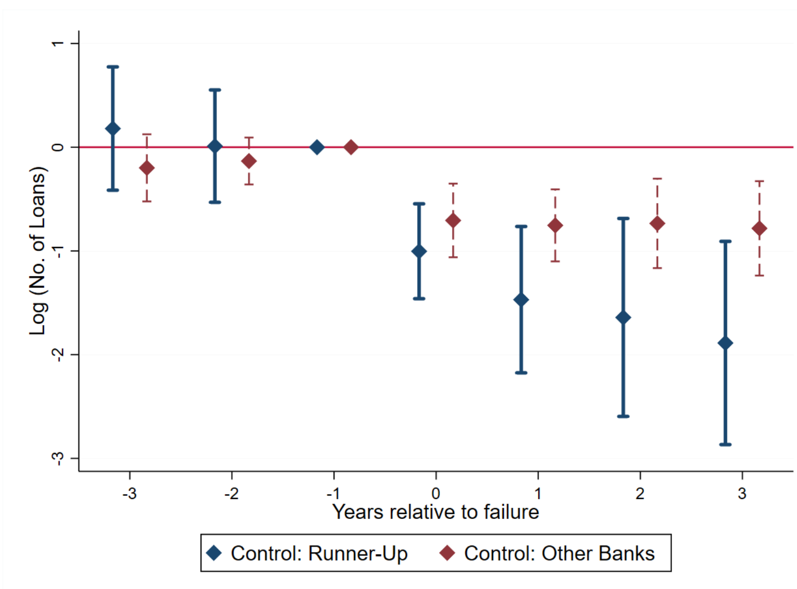
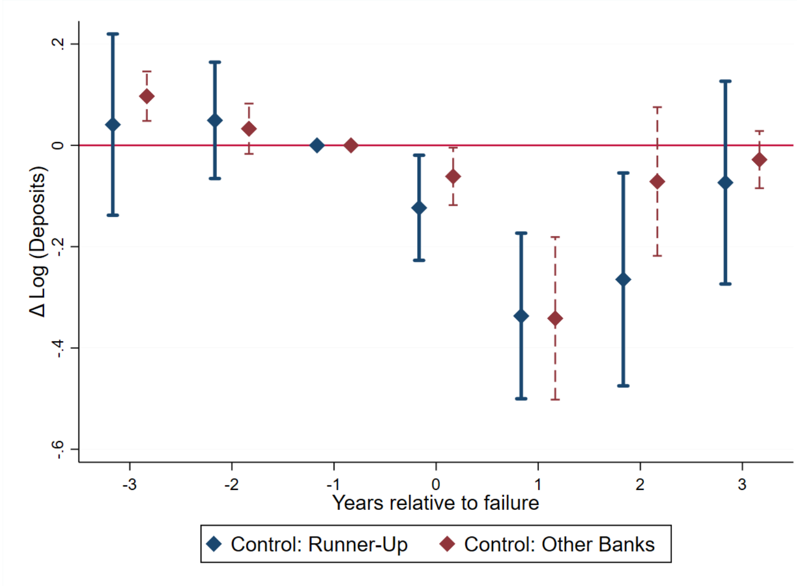


Figure 9: **Dynamics of Small Business Lending in Failed Bank Markets**
The figure plots the coefficients from the following dynamic regression:

$$Y_{fbt} = \alpha_{fb} + \gamma_t + \sum_{\tau=-3}^{\tau=3} \delta_\tau (D_{bt}^\tau \times \text{WIN}_{bt}) + \varepsilon_{fbt}$$

The sample is restricted to bank failures in which the auction was competitive. The blue (maroon) markers represent estimates from regressions in which the control group is the runner-up (all other) banks. Failure-bidder and year fixed effects are included and clustering is at the failure-bidder level.

(a) Target Only



(b) Target+Acquirer

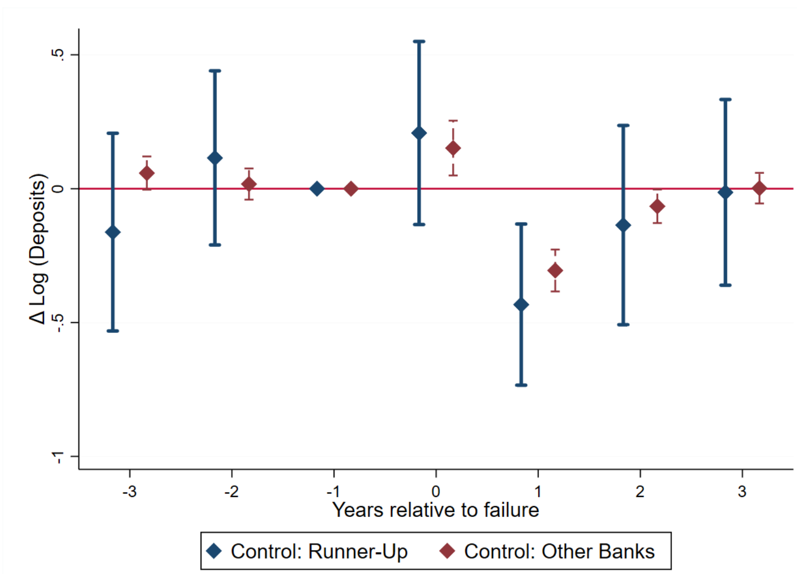


Figure 10: **Dynamics of Deposit Flows in Failed Bank Markets**
The figure plots the coefficients from the following dynamic regression:

$$Y_{fbt} = \alpha_{fb} + \gamma_t + \sum_{\tau=-3}^{\tau=3} \delta_\tau (D_{bt}^{\tau} \times \text{WIN}_{bt}) + \varepsilon_{fbt}$$

The sample is restricted to bank failures in which the auction was competitive. The blue (maroon) markers represent estimates from regressions in which the control group is the runner-up (all other) banks. Failure-bidder and year fixed effects are included and clustering is at the failure-bidder level.

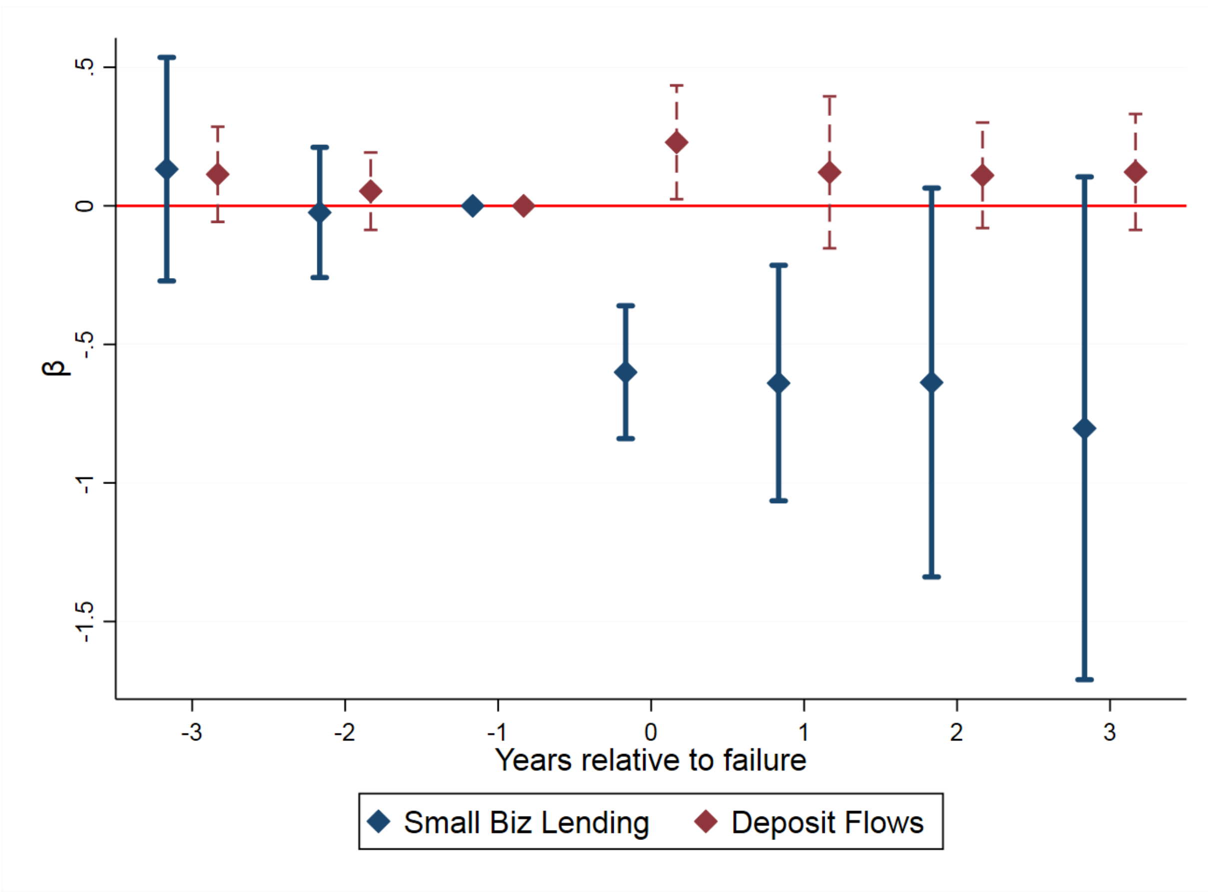


Figure 11: **Lending and Deposit Flows in Consolidated vs. Unconsolidated markets**

The figure plots the coefficients from the following dynamic regression:

$$Y_{bfct} = \alpha_{bfc} + \gamma_t + \sum_{\tau=-3}^{\tau=3} \delta_\tau (D^{\tau}_{ft} \times \text{Treat}_{bc}) + \varepsilon_{bfct}$$

The sample is restricted to bank failures in which the auction was competitive, and only to failed bank counties that had one of either the winning or runner-up bank present in the year before failure. $Treat_{bc}$ takes the value 1 for counties in which the the winning bank and failed bank were present, and 0 for counties in which the runner-up bank and failed bank were present. Failure-bidder-county and year fixed effects are included and clustering is at the failure-bidder level.

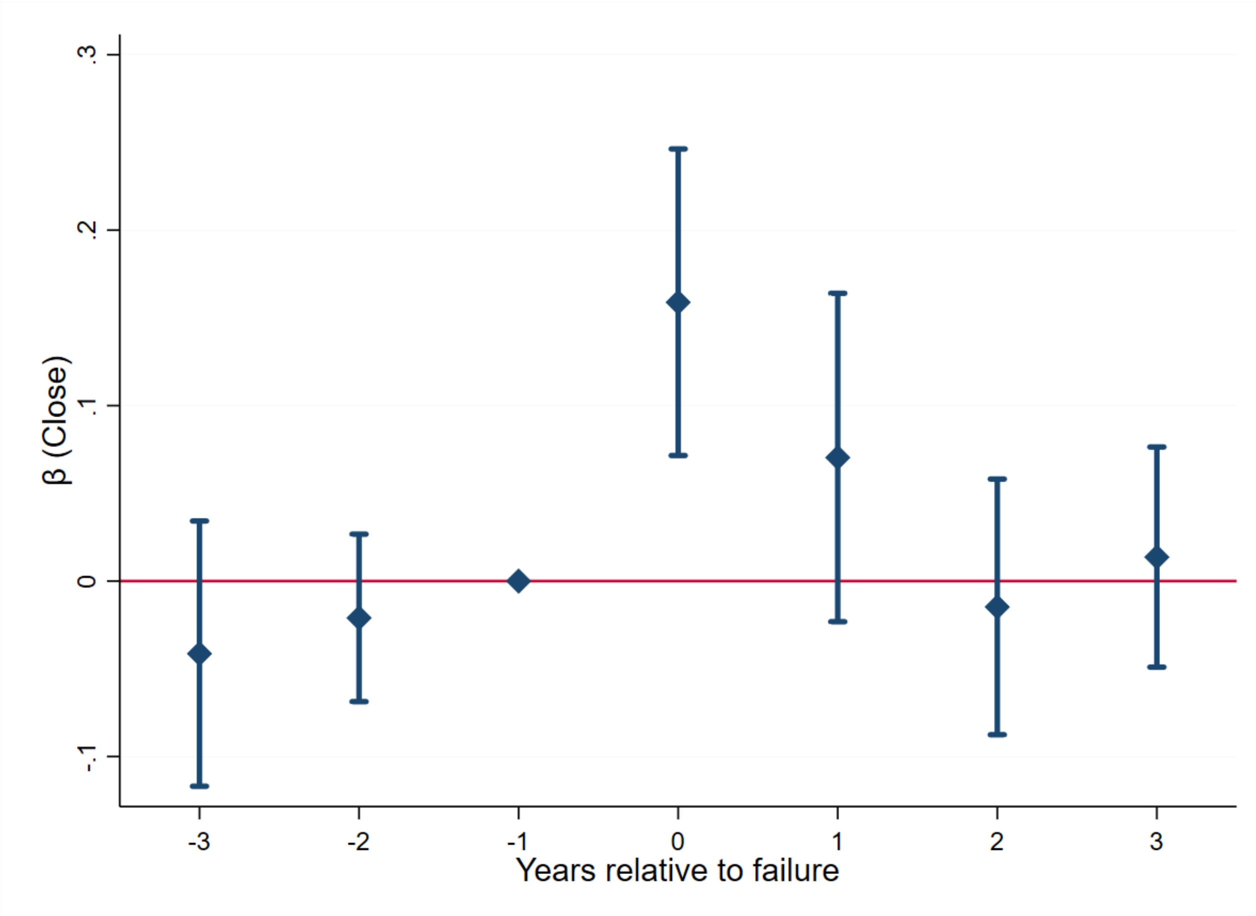


Figure 12: **Dynamics of Failed Bank branch closings**
The figure plots the coefficients from the following dynamic regression:

$$Close_{ufct} = \alpha_u + \gamma_{ct} + \sum_{\tau=-3}^{\tau=3} \delta_\tau (D^{\tau}_{ft} \times \text{Treat}_{uc}) + \varepsilon_{ufct}$$

The unit of observation is the branch-year level. The sample is restricted to bank failures in which the auction was competitive, and includes failed bank branches only in counties that had an overlap with either the winner (treated) or runner-up bank's (control) branch network. Branch and county-year fixed effects are included and clustering is at the county level.

Table 1: **Summary Statistics: Failed Banks**

The table below has summary statistics on all banks in the 50 states that failed between 2007 and 2016. Financial information is for the latest quarter before failure that it is available. Variable definitions are in Appendix Table A.1.

Panel A: All Failures

	N	Mean	SD	P25	P50	P75
Assets (mn)	518	708.5	2244.3	98.6	208.6	489.0
No. of branches	518	8.307	21.347	2	4	7
State Bank	518	0.809	0.394	1	1	1
Deposits Ratio	518	0.914	0.081	0.875	0.933	0.974
Core Deposits Ratio	518	0.657	0.145	0.557	0.659	0.763
Tier 1 Capital Ratio	517	0.015	0.049	0.003	0.017	0.029
Liquidity Ratio	518	0.220	0.098	0.149	0.208	0.269
Residential Loans (%)	518	26.135	19.526	11.998	23.108	32.736
CRE Loans (%)	518	33.300	16.901	21.723	31.945	43.318
C&I Loans (%)	518	10.715	9.645	4.330	8.352	14.238
Consumer Loans (%)	518	2.122	3.080	0.350	1.066	2.658
30-89PD Ratio (%)	518	4.584	3.610	2.208	3.867	6.117
NPL Ratio (%)	518	16.228	9.581	9.415	14.713	20.298
OREO Ratio (%)	518	5.114	4.822	1.572	3.778	7.229
Unused Commitment Ratio (%)	518	7.044	6.619	3.174	5.636	9.317
Cost to FDIC	518	0.246	0.137	0.143	0.233	0.338

Panel B: Sample of Failures with Competitive Auctions

	N	Mean	SD	P25	P50	P75
Assets (mn)	244	669.4	2074.7	96.3	193.2	443.7
No. of branches	244	9.357	25.594	2	4	8
State Bank	244	0.770	0.421	1	1	1
Deposits Ratio	244	0.917	0.077	0.877	0.938	0.976
Core Deposits Ratio	244	0.662	0.144	0.550	0.667	0.773
Tier 1 Capital Ratio	244	0.013	0.035	0.003	0.016	0.027
Liquidity Ratio	244	0.231	0.093	0.164	0.225	0.277
Residential Loans (%)	244	26.300	16.906	14.689	23.915	32.889
CRE Loans (%)	244	36.010	16.514	25.049	34.513	45.267
C&I Loans (%)	244	10.256	8.565	4.244	7.990	14.067
Consumer Loans (%)	244	2.080	2.944	0.459	1.157	2.616
30-89PD Ratio (%)	244	4.078	3.375	1.757	3.212	5.457
NPL Ratio (%)	244	15.358	8.785	9.127	14.259	19.701
OREO Ratio (%)	244	5.523	5.218	1.845	3.998	7.646
Unused Commitment Ratio (%)	244	6.807	6.449	3.294	5.549	9.014
Cost to FDIC	244	0.200	0.106	0.119	0.196	0.270

Table 2: **Difference in Means: Bidders**

The table compares characteristics for bidding banks that won the auction for a failed bank against those that came second. The characteristic is measured at the last period before the failure of the bank being bid for. The first (second) column has the mean value of each characteristic and its standard deviation in parentheses for the winner (runner-up) sample. The third column has the point estimate and standard error (in parentheses) for a t-test comparing the means of the two samples.

	Winner	Runner-Up	Diff in Means
Log (Assets)	21.325	21.081	0.245
	[1.880]	[1.540]	(0.158)
Deposits Ratio	0.788	0.796	-0.008
	[0.082]	[0.075]	(0.007)
Core Deposits Ratio	0.634	0.647	-0.012
	[0.096]	[0.084]	(0.008)
State Bank	0.667	0.688	-0.021
	[0.472]	[0.464]	(0.043)
Dist between closest branches (km.)	155.374	227.678	-72.304
	[446.120]	[638.615]	(50.816)
County Branch Overlap	0.527	0.473	0.055
	[0.500]	[0.500]	(0.046)
Tier 1 Capital Ratio	0.176	0.160	0.015
	[0.112]	[0.074]	(0.009)
Liquidity Ratio	0.259	0.237	0.022*
	[0.122]	[0.106]	(0.011)
Residential Loans (%)	24.450	24.965	-0.515
	[14.060]	[15.124]	(1.341)
CRE Loans (%)	33.673	34.084	-0.411
	[14.201]	[13.928]	(1.292)
C and I Loans (%)	14.684	14.571	0.113
	[8.535]	[9.508]	(0.830)
Consumer Loans (%)	5.470	5.243	0.227
	[8.622]	[8.728]	(0.797)
30-89PD Ratio (%)	1.357	1.365	-0.008
	[1.297]	[1.220]	(0.116)
NPL Ratio (%)	4.489	3.976	0.513
	[5.616]	[4.419]	(0.464)
OREO Ratio (%)	1.110	1.069	0.041
	[1.355]	[1.154]	(0.116)
Unused Commitment Ratio (%)	16.631	15.387	1.244
	[9.958]	[7.079]	(0.794)
Deposit Premium (%)	0.367	0.360	0.008
	[1.003]	[0.793]	(0.086)
Asset Discount(%)	-12.438	-14.450	2.012*
	[9.069]	[9.866]	(0.915)
Bid Value(%)	-12.124	-14.163	2.038*
	[9.203]	[9.954]	(0.926)
Observations	237	237	474

Table 3: **Event Study around Failure announcements**

The sample is restricted to bank failures in which the bidding was competitive, and stock return data is available for bidders. A market model is used for estimation with the value-weighted market return proxying for the market return. The estimation window is 200 trading days and ends 11 trading days before the announcement date. In the event study, cumulative abnormal return (CAR) is calculated over the specified trading window. To mitigate the effect of outliers, the CAR variable is winsorised at 2.5% and 97.5%. The indicator , *Winner*, takes the value 1 for the bank that won a particular auction, and 0 for the bank that lost. The returns are in percentage points. Failed bank fixed effects are included. Standard errors clustered at the failed bank level are in brackets. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

	Return Window				
	[-2,0]	[-1,0]	[0]	[0,+1]	[0,+2]
CAR*Winner	0.243	0.402	0.219	1.693***	1.724**
	(0.604)	(0.491)	(0.257)	(0.587)	(0.666)
CAR	-0.059	-0.076	0.045	-0.252	0.007
	(0.165)	(0.134)	(0.070)	(0.160)	(0.182)
Observations	363	363	363	363	363
R^2	0.710	0.690	0.734	0.683	0.679

Table 4: **Bank-level effects of Acquiring a Failed Bank**

The table reports the coefficients from the following regression:

$$Y_{fbt} = \alpha_{fb} + \gamma_t + WIN_{fb} \times POST_t + \varepsilon_{fbt}$$

The sample is restricted to bank failures in which the auction was competitive. Panel A includes all banks while Panel B includes only the winner and runner-up bidder. Failure-bidder and quarter fixed effects are included and clustering is at the failure-bidder level. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

Panel A: All Banks

	Dependent Variable							
	Log Assets (1)	Dep/TA (2)	CoreDep/TA (3)	Loans/TA (4)	Liq Ratio (5)	T1Cap (6)	RELoans/TA (7)	CILoans/TA (8)
Winner*Post	0.254***	0.016***	0.017***	-0.002	-0.015***	-0.012**	0.004	-0.003*
	(0.030)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)	(0.002)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Failure-Bidder FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12852505	12852505	12852505	12852505	12852505	12836981	12852505	12852505
R^2	0.996	0.946	0.948	0.961	0.952	0.766	0.979	0.962

Panel B: Winner and Loser

	Dependent Variable							
	Log Assets (1)	Dep/TA (2)	CoreDep/TA (3)	Loans/TA (4)	Liq Ratio (5)	T1Cap (6)	RELoans/TA (7)	CILoans/TA (8)
Winner*Post	0.167***	0.011***	0.007**	-0.004	-0.010**	-0.008	0.004	-0.004*
	(0.030)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)	(0.002)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Failure-Bidder FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3393	3393	3393	3393	3393	3393	3393	3393
R^2	0.983	0.911	0.909	0.908	0.902	0.825	0.945	0.936

Table 5: **Small Business Lending Consequences of Acquiring a Failed Bank: Bank regressions**

The table reports the coefficients from the following regression:

$$Loans_{fbt} = \alpha_{fb} + \gamma_t + WIN_{fbt} \times POST_{fbt} + \varepsilon_{fbct}$$

The sample is restricted to bank failures in which the auction was competitive, and to small business lending at the bank level. A *Target Only* market is a county in which the failed bank had lending in the year prior to failure but the Acquirer did not. A *Target+Acquirer* market is a county in which the failed bank and the acquirer had lending in the year prior to failure. An *Acquirer Only* market is a county in which the the acquirer had lending in the year prior to failure but the failed bank did not. Failure-bidder and year fixed effects are included and clustering is at the failure-bidder level. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

	Small Biz Lending: Log Amount					
	Target Only		Target+Acquirer		Acquirer Only	
Winner*Post	-1.736***	-1.377**	-0.426***	-1.186***	0.206***	-0.018
	(0.511)	(0.640)	(0.156)	(0.406)	(0.063)	(0.077)
Banks	All	Top 2	All	Top 2	All	Top 2
Failure-Bank FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	30879	293	40201	269	723021	1841
R^2	0.807	0.783	0.804	0.870	0.847	0.890

	Small Biz Lending: Log Number					
	Target Only		Target+Acquirer		Acquirer Only	
Winner*Post	-1.296***	-1.109**	-0.520***	-1.036***	0.167***	-0.009
	(0.348)	(0.427)	(0.143)	(0.313)	(0.056)	(0.069)
Banks	All	Top 2	All	Top 2	All	Top 2
Failure-Bank FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	30879	293	40201	269	723021	1841
R^2	0.906	0.813	0.915	0.907	0.942	0.937

Table 6: **Small Business Lending Consequences of Acquiring a Failed Bank: Bank-county regressions**

The table reports the coefficients from the following regression:

$$Loans_{fbct} = \alpha_{fb} + \gamma_{ct} + WIN_{bct} \times POST_{ft} + \varepsilon_{fbct}$$

The sample is restricted to bank failures in which the auction was competitive, and to small business lending at the bank-county level. A *Target Only* market is a county in which the failed bank had lending in the year prior to failure but the Acquirer did not. A *Target+Acquirer* market is a county in which the failed bank and the acquirer had lending in the year prior to failure. An *Acquirer Only* market is a county in which the the acquirer had lending in the year prior to failure but the failed bank did not. Failure-bidder-county and county-year fixed effects are included and clustering is at the failure-bidder level. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

	Small Biz Lending: Log (Number)					
	Target Only		Target+Acquirer		Acquirer Only	
Winner*Post	-1.407***	-1.831***	-0.092	-2.209***	-0.127**	-0.035
	(0.382)	(0.621)	(0.191)	(0.476)	(0.051)	(0.024)
Banks	All	Top 2	All	Top 2	All	Top 2
Bank-County FE	Y	Y	Y	Y	Y	Y
Cty-Year FE	Y	Y	Y	Y	Y	Y
Observations	36594	230	56246	764	3919686	60095
R^2	0.790	0.786	0.771	0.856	0.775	0.945

	Small Biz Lending: Log (Number)					
	Target Only		Target+Acquirer		Acquirer Only	
Winner*Post	-1.018***	-1.645***	-0.143	-1.319***	-0.112	-0.061
	(0.150)	(0.366)	(0.132)	(0.238)	(0.080)	(0.045)
Banks	All	Top 2	All	Top 2	All	Top 2
Bank-County FE	Y	Y	Y	Y	Y	Y
Cty-Year FE	Y	Y	Y	Y	Y	Y
Observations	36594	230	56246	764	3919686	60095
R^2	0.802	0.887	0.801	0.915	0.747	0.954

Table 7: **Aggregate Small Business Lending Consequences: County regressions**

The table reports the coefficients from the following regression:

$$Loans_{ct} = \alpha_c + \gamma_t + FB_c \times POST_t + \varepsilon_{ct}$$

The table shows results from regressions relating aggregate small business lending at the county-year level to the presence of a lender that failed. *FailedBank* is an indicator taking the value 1 if a failed bank was operating in the county in the year before it failed, and 0 otherwise. *Share of Failed Bank Lending* is the share of the county's total small business lending that was done by the failed bank in the year before its failure. *Post* takes the value 1 for the periods after failure, and 0 otherwise. County fixed effects are included in all specifications. Year (State-year) fixed effects are in odd (even) numbered columns. Clustering is at the county level. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

	Total Small Business Lending			
	Log (Amount)			
FailedBank*Post	-0.001	0.004		
	(0.009)	(0.010)		
Share of FailedBankLending*Post			-0.223***	-0.218***
			(0.058)	(0.060)
County & Year FE	Y	Y	Y	Y
State-Year FE	-	Y	-	Y
Observations	35429	35392	3641	3593
R^2	0.948	0.953	0.986	0.989

	Total Small Business Lending			
	Log (Number)			
FailedBank*Post	-0.019***	-0.012**		
	(0.006)	(0.006)		
Share of FailedBankLending*Post			-0.449***	-0.426***
			(0.085)	(0.088)
County & Year FE	Y	Y	Y	Y
State-Year FE	-	Y	-	Y
Observations	35430	35393	35430	35393
R^2	0.978	0.982	0.978	0.982

Table 8: **Deposit Flows on Acquiring a Failed Bank**

The table reports the coefficients from the following regression:

$$\Delta LogDep_{fbct} = \alpha_{fbc} + \gamma_{ct} + WIN_{fbc} \times POST_t + \varepsilon_{fbct}$$

The sample is restricted to bank failures in which the auction was competitive, and to deposit flows at the bank-county level. A *Target Only* market is a county in which the failed bank had lending in the year prior to failure but the Acquirer did not. A *Target+Acquirer* market is a county in which the failed bank and the acquirer had lending in the year prior to failure. An *Acquirer Only* market is a county in which the the acquirer had lending in the year prior to failure but the failed bank did not. Failure-bidder-county and county-year fixed effects are included and clustering is at the failure-bidder level. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

	Δ Log Deposits					
	Target Only		Target+Acquirer		Acquirer Only	
Winner*Post	-0.167***	-0.141***	-0.054**	-0.119***	0.077***	0.017
	(0.031)	(0.049)	(0.024)	(0.040)	(0.009)	(0.013)
Bank-Cty FE	Y	Y	Y	Y	Y	Y
Year FE	All	Top 2 Bidders	All	Top 2 Bidders	All	Top 2 Bidders
Cty-Year FE	Y	Y	Y	Y	Y	Y
Observations	82860	2411	68732	1412	43638294	93673
R^2	0.323	0.547	0.300	0.557	0.337	0.685

Table 9: **Deposit Rates on Acquiring a Failed Bank**

The table reports the coefficients from the following regression:

$$DepRate_{fbct} = \alpha_{fbc} + \gamma_{ct} + WIN_{fbc} \times POST_t + \varepsilon_{fbct}$$

The sample is restricted to bank failures in which the auction was competitive, and to deposit rates at the bank-county level. The deposit rate I use in benchmark regressions is the rate on 12 month CDs with an account size of $ 10,000. A *Target Only* market is a county in which the failed bank had lending in the year prior to failure but the Acquirer did not. A *Target+Acquirer* market is a county in which the failed bank and the acquirer had lending in the year prior to failure. An *Acquirer Only* market is a county in which the the acquirer had lending in the year prior to failure but the failed bank did not. Failure-bidder-county and county-quarter fixed effects are included and clustering is at the failure-bidder level. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

	Deposit Rates					
	Target Only		Target + Acquirer		Acquirer Only	
Winner*Post	-0.137***	-0.149	-0.127**	-0.015	0.005	-0.096**
	(0.036)	(0.094)	(0.052)	(0.074)	(0.036)	(0.049)
Bank-Cty FE	Y	Y	Y	Y	Y	Y
Qtr FE	All	Top 2 Bidders	All	Top 2 Bidders	All	Top 2 Bidders
Cty-Qtr FE	Y	Y	Y	Y	Y	Y
Observations	15008	575	18216	589	319633	17146
R^2	0.929	0.937	0.914	0.899	0.920	0.933

Table 10: **Effects of Consolidation on Lending and Deposits**

The table reports the coefficients from the following regression:

$$Y_{fbct} = \alpha_{fbc} + \gamma_t + \beta Treat_{bc} \times POST_{ft} + \varepsilon_{fbct}$$

The sample is restricted to bank failures in which the auction was competitive, and only to failed bank counties that had one of either the winning or runner-up bank present in the year before failure. $Treat_{bc}$ takes the value 1 for counties in which the the winning bank and failed bank were present, and 0 for counties in which the runner-up bank and failed bank were present. Failure-bidder-county and year fixed effects are included and clustering is at the failure-bidder level. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

	Log SB Loan No.		Δ Log Deposits		Deposit Rate	
Treat*Post	-0.606***	-0.570***	0.000	-0.012	-0.036	-0.082
	(0.188)	(0.206)	(0.040)	(0.037)	(0.034)	(0.060)
Bank-Cty FE	Y	Y	Y	Y	Y	Y
Year FE	Y	-	Y	-	Y	-
State-Year FE	N	Y	N	Y	N	Y
Observations	3171	3124	2543	2485	1060	334
R^2	0.837	0.886	0.229	0.338	0.914	0.938

Appendices

A Data and Summary Stats

Table A.1: **Variable Definitions**

Variable	Definition
Balance Sheet	
Deposits Ratio	Ratio of domestic deposits (*depdom*) to assets (*asset*)
Core Deposits Ratio	Domestic deposits (*depdom*) less large time deposits(*ntrtmlg*) scaled by assets (*asset*)
Tier 1 Capital Ratio	Ratio of Tier 1 capital (*rbct1j*) to risk-weighted assets (*rwajt*)
Liquidity Ratio	Sum of cash (*chbal*), fed funds sold(*frepo*) and securities available-for-sale (*scaf*) scaled by assets (*asset*)
Residential Loans (%)	Ratio of 1-4 family residential loans (*lnreres*) to total loans and leases (*lnlsgr*), expressed as a percentage
CRE Loans (%)	Ratio of commercial real estate loans (*lnrenres*) to total loans and leases (*lnlsgr*), expressed as a percentage
C&I Loans (%)	Ratio of commercial and industrial loans (*lnci*) to total loans and leases (*lnlsgr*), expressed as a percentage
Consumer Loans (%)	Ratio of loans to individuals (*lncon*) to total loans and leases (*lnlsgr*), expressed as a percentage
30-89PD Ratio (%)	Ratio of assets past due 30-89 days (*p3asset*) to assets (*asset*), expressed as a percentage
NPL Ratio (%)	Sum of nonaccrual assets (*naasset*) and assets past due more than 90 days (*p9asset*) scaled by assets (*asset*), expressed as a percentage
OREO Ratio (%)	Ratio of other real estate owned (*ore*) to assets (*asset*), expressed as a percentage
Unused Commitment Ratio (%)	Unused commitments (*uc*) scaled by sum of unused commitments and total loans and leases (*lnlsgr*), expressed as a percentage
State Bank	Indicator for banks regulated at the state level. Takes value 1 if charter class is not "N" or "SA"

Table A.1: **Variable Definitions** (contd.)

Variable	Definition
Branch Network	
No. of branches	Count of physical bank branches for a bank in the Summary of Deposits of a given year
Distance between closest branches (km.)	For a pair of banks, it is the minimum of the geographic distance for each pair of branches belonging to the two banks. Distance is calculated using the Haversine formula.
County (Zip) Branch Overlap	For a pair of banks, it is an indicator taking value 1 if both banks have at least one branch in the same county (zip code)
Bidding process	
Cost to FDIC	For a failed bank, it is the FDIC's estimated cost to the Deposit Insurance Fund scaled by the bank's assets in the quarter preceding resolution
Deposit Premium (%)	In a bid, it is the deposit premium expressed in dollars scaled by the assets of the failed bank, expressed as a percentage
Asset Discount(%)	In a bid, it is the asset discount expressed in dollars scaled by the assets of the failed bank, expressed as a percentage
Bid Value (%)	In a bid, it is the sum of the asset discount and the deposit premium, both expressed as a percentage of the failed bank's assets

Table A.2: **Difference in Means: Competitive and non-competitive auctions**

The table compares characteristics for failed banks that were sold in competitive auctions against those sold in non-competitive auctions. A competitive auction is one in which at least two distinct banks can be identified as bidders. The first (second) column has the mean value of each characteristic and its standard deviation in parentheses for the winner (runner-up) sample. The third column has the point estimate and standard error (in parentheses) for a t-test comparing the means of the two samples.

	Comp Bid	Non-Comp Bid	Diff of Means
Assets (mn)	669.4	468.8	200.6
	[2074.7]	[1106.8]	(154.9)
No. of branches	9.357	6.461	2.895
	[25.594]	[13.597]	(1.909)
State Bank	0.770	0.850	-0.079*
	[0.421]	[0.358]	(0.037)
Deposits Ratio	0.917	0.922	-0.005
	[0.077]	[0.074]	(0.007)
Core Deposits Ratio	0.662	0.635	0.027
	[0.144]	[0.142]	(0.014)
Tier 1 Capital Ratio	0.013	0.010	0.003
	[0.035]	[0.037]	(0.003)
Liquidity Ratio	0.231	0.204	0.027**
	[0.093]	[0.083]	(0.008)
Residential Loans (%)	26.300	25.495	0.805
	[16.906]	[18.534]	(1.718)
CRE Loans (%)	36.010	33.812	2.198
	[16.514]	[16.536]	(1.592)
C&I Loans (%)	10.256	10.979	-0.722
	[8.565]	[8.771]	(0.836)
Consumer Loans (%)	2.080	2.217	-0.136
	[2.944]	[3.188]	(0.297)
30-89PD Ratio (%)	4.078	4.891	-0.813*
	[3.375]	[3.345]	(0.324)
NPL Ratio (%)	15.358	17.228	-1.870*
	[8.785]	[9.691]	(0.896)
OREO Ratio (%)	5.523	5.303	0.220
	[5.218]	[4.638]	(0.472)
Unused Commitment Ratio (%)	6.807	6.368	0.439
	[6.449]	[4.933]	(0.545)
Cost to FDIC	0.200	0.282	-0.082***
	[0.106]	[0.135]	(0.012)
Observations	244	193	437

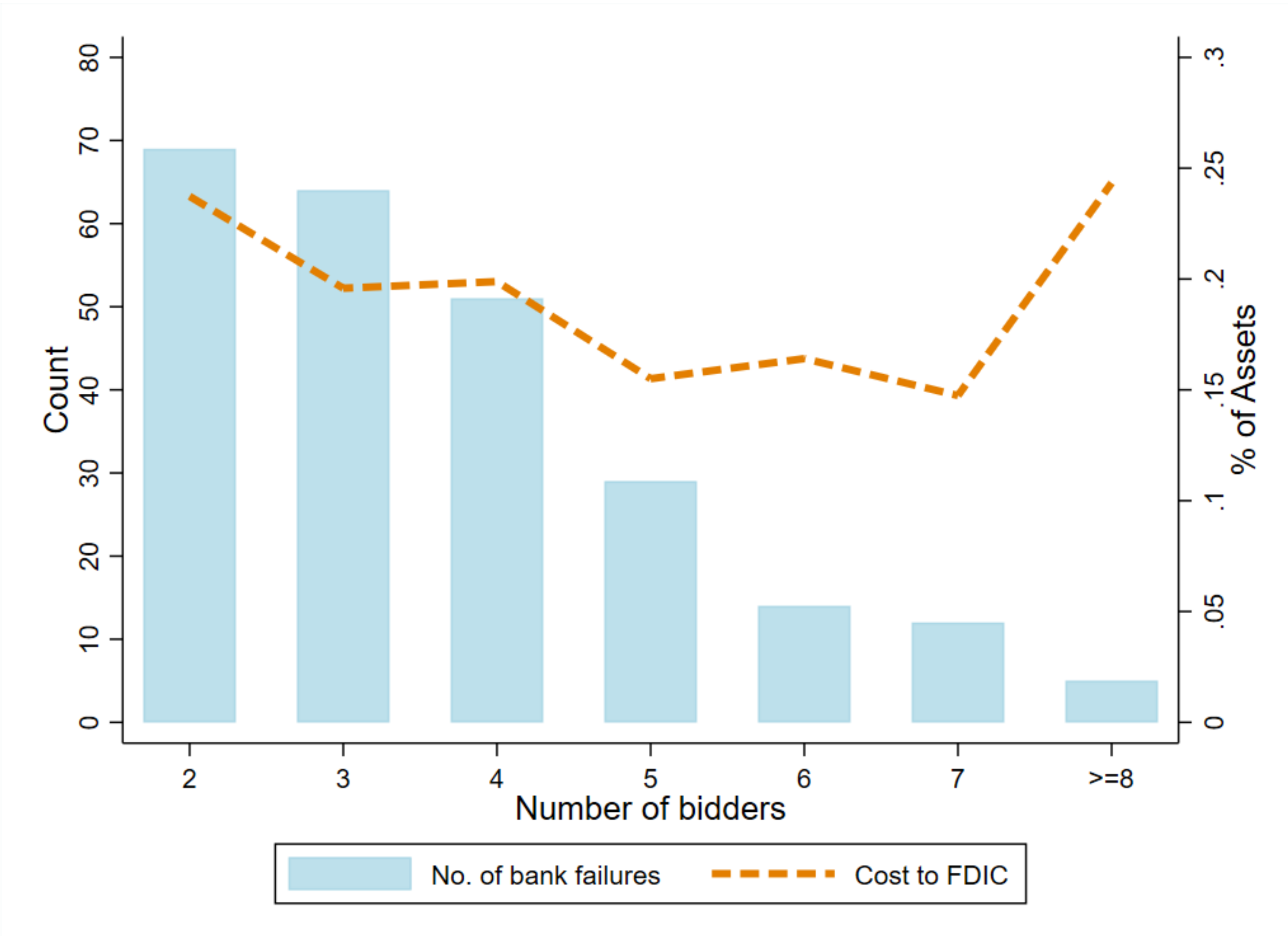


Figure A.1: **Competitiveness of failed bank auctions**
The figure shows, for the sample of competitive auctions, the distribution of the number of participating bidder banks as well as the average cost to FDIC by number of bidders. *Data source: FDIC*

B Illustrations

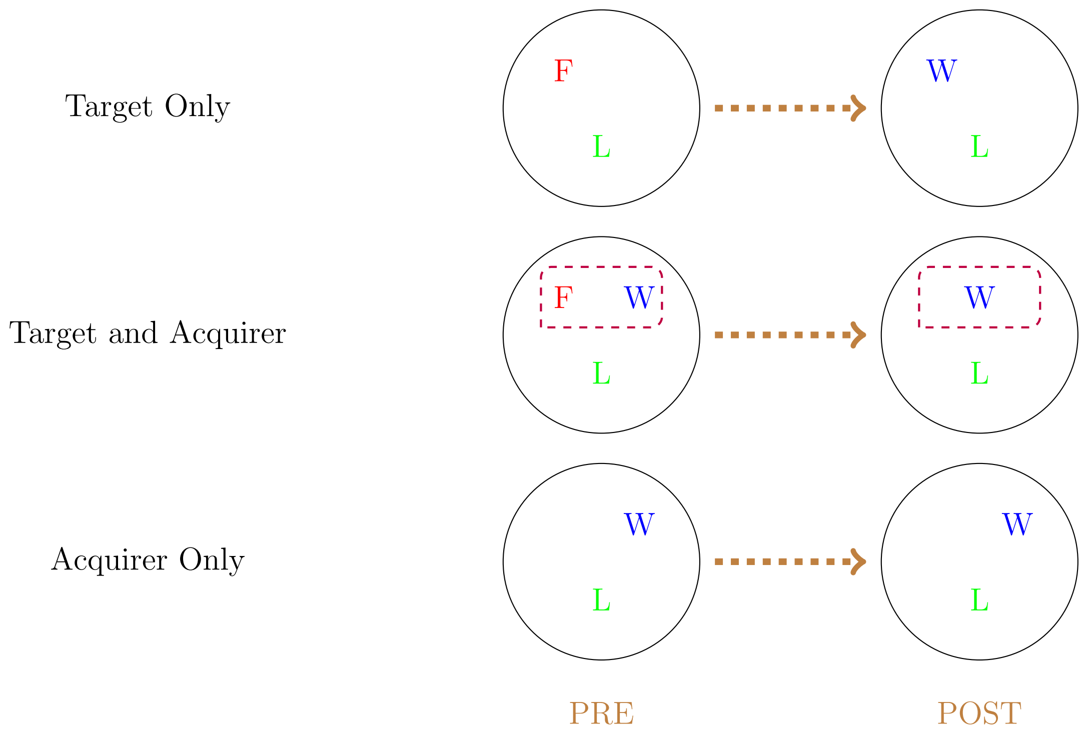


Figure B.1: **Different types of Market Structure**

The figure illustrates the different types of banking markets based on the pre-acquisition presence of the acquiring bank and the target bank, and how they change after acquisition. A circle represents a county. *F* represents the Failed Bank, *W* represents the Winning Bank and *L* represents Other (or Losing) Banks. In 'Target Only' markets, F and L banks are present prior to acquisition and W and L banks are present after acquisition. In 'Target and Acquirer' markets, F, W and L banks are present prior to acquisition but only W and L banks are present after acquisition. In 'Acquirer Only' markets, W and L banks are present both before and after acquisition. F banks are not present.

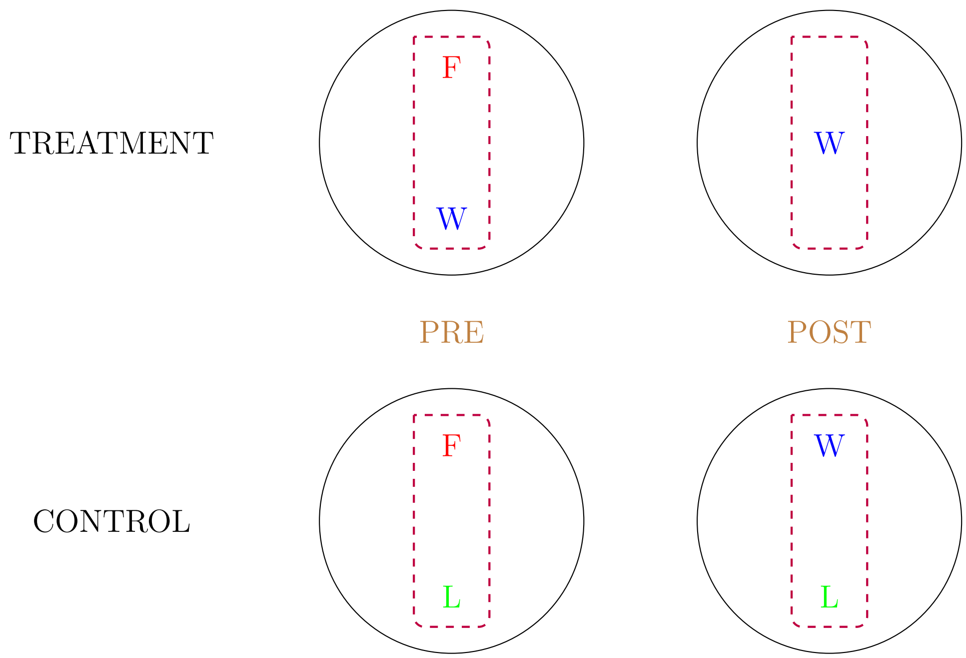


Figure B.2: **Consolidated and Unconsolidated Markets**
The figure illustrates the empirical strategy used to identify the effect of consolidation A circle represents a county. F represents the Failed Bank, W represents the Winning Bank and L represents the Runner-Up Bank. Treated markets are those in which F and W banks are present prior to acquisition and only W banks are present after. L banks are not present in treated markets. Control markets are those in which F and L banks are present prior to acquisition and W and L banks are present after.

C Mortgage Lending Results

Table C.1: **Mortgage Lending Consequences of Acquiring a Failed Bank: Bank-county regressions**

The table reports the coefficients from the following regression:

$$Loans_{fbct} = \alpha_{fb} + \gamma_{ct} + WIN_{bct} \times POST_{ft} + \varepsilon_{fbct}$$

The sample is restricted to bank failures in which the auction was competitive, and to mortgage lending at the bank-county level. A *Target Only* market is a county in which the failed bank had lending in the year prior to failure but the Acquirer did not. A *Target+Acquirer* market is a county in which the failed bank and the acquirer had lending in the year prior to failure. An *Acquirer Only* market is a county in which the the acquirer had lending in the year prior to failure but the failed bank did not. Failure-bidder-county and county-year fixed effects are included and clustering is at the failure-bidder level. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

	Mortgage Lending: Log (Amount)					
	Target Only		Target+Acquirer		Acquirer Only	
Winner*Post	-2.130***	-1.746***	-0.382***	-0.547***	0.265***	0.053
	(0.351)	(0.411)	(0.092)	(0.198)	(0.066)	(0.104)
Banks	All	Top 2	All	Top 2	All	Top 2
Bank-Cty FE	Y	Y	Y	Y	Y	Y
Cty-Year FE	Y	Y	Y	Y	Y	Y
Observations	436199	6462	248940	2419	7170877	93980
R^2	0.722	0.822	0.735	0.838	0.703	0.891

	Mortgage Lending: Log (Number)					
	Target Only		Target+Acquirer		Acquirer Only	
Winner*Post	-1.640***	-2.079***	-0.081	-0.822***	0.298***	0.062
	(0.103)	(0.208)	(0.078)	(0.149)	(0.055)	(0.085)
Banks	All	Top 2	All	Top 2	All	Top 2
Bank-Cty FE	Y	Y	Y	Y	Y	Y
Cty-Year FE	Y	Y	Y	Y	Y	Y
Observations	436199	6462	248940	2419	7170877	93980
R^2	0.804	0.906	0.808	0.904	0.797	0.921

Table C.2: **Mortgage Lending Consequences of Acquiring a Failed Bank: Bank regressions**

The table reports the coefficients from the following regression:

$$Loans_{fbt} = \alpha_{fb} + \gamma_t + WIN_{fbt} \times POST_{fbt} + \varepsilon_{fbct}$$

The sample is restricted to bank failures in which the auction was competitive, and to mortgage lending at the bank level. A *Target Only* market is a county in which the failed bank had lending in the year prior to failure but the Acquirer did not. A *Target+Acquirer* market is a county in which the failed bank and the acquirer had lending in the year prior to failure. An *Acquirer Only* market is a county in which the the acquirer had lending in the year prior to failure but the failed bank did not. Failure-bidder and year fixed effects are included and clustering is at the failure-bidder level. Significance levels: *(p<0.10), **(p<0.05), *** (p<0.01)

	Mortgage Lending: Log Amount					
	Target Only		Target+Acquirer		Acquirer Only	
Winner*Post	-0.971***	-0.760***	-0.300**	-0.694***	0.374***	0.065
	(0.207)	(0.240)	(0.130)	(0.166)	(0.087)	(0.104)
Banks	All	Top 2	All	Top 2	All	Top 2
Failure-Bank FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	237669	1307	256398	1422	2521592	2742
R^2	0.802	0.739	0.800	0.821	0.821	0.889

	Mortgage Lending: Log Number					
	Target Only		Target+Acquirer		Acquirer Only	
Winner*Post	-0.690***	-0.464***	-0.275***	-0.538***	0.342***	0.039
	(0.128)	(0.136)	(0.100)	(0.120)	(0.067)	(0.076)
Banks	All	Top 2	All	Top 2	All	Top 2
Failure-Bank FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	237669	1307	256398	1422	2521592	2742
R^2	0.896	0.845	0.886	0.884	0.912	0.936