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ABSTRACT

We study the recent episode of bank failures and provide simple facts to better understand who acquires failed banks and which forces drive the losses that the FDIC realizes from these sales. We document three distinct forces related to the allocation of failed banks to potential acquirers. First, a geographically proximate bank is significantly more likely to acquire a failed bank: only 15% of acquirers do not have branches within the state. Sales are more local in regions with more soft information. Second, a failed bank is more likely to be purchased by a bank that has a similar loan portfolio and that offers similar services, highlighting the role of failed banks' asset specificity. Third, low capitalization of potential acquirers decreases their ability to acquire a failed bank and potentially distorts failed bank allocation. The results are robust to restricting the data to actual bidders, confirming that they are not driven by auction eligibility criteria imposed by the FDIC. We relate these forces to FDIC losses from failed bank sales. We organize these facts using the fire sales framework of Shleifer and Vishny (1992). Our findings speak to recent policies that are predicated on the idea that a bank's ability to lend is embodied in its collection of assets and employees and cannot be easily replaced or sold.

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I. Introduction

The great recession and its aftermath saw an unprecedented number of banks being taken into receivership by the FDIC and then sold at auctions. These failures impose substantial costs on the FDIC: the average cost of a sold failed bank from 2007 to 2013 was approximately 28% of the failed bank's assets. The resolution of bank failures led to Deposit Insurance Fund costs of approximately $90 billion, leaving the fund with a negative balance of almost $21 billion at the height of the crisis in 2009 (Davison and Carreon, 2010). Small and medium-sized banks, which are typically sold at FDIC auctions, have also been large beneficiaries of government programs during the same period.[1] For example, the Treasury department does not expect to recover all of the $791 million of TARP funds that were awarded to 26 failed banks in our sample (Office of the Special Inspector General for the Troubled Asset Relief Program, 2014). In spite of the importance of failed bank resolutions during the recent crisis, little is known about the forces that affect sales of failed banks since the S&L crisis (James and Wier, 1987; James, 1991).

The goal of this paper is to study the recent episode of bank failures and provide simple facts that allow us to understand who acquires failed banks and which forces drive the losses that the FDIC realizes from these sales. We document three distinct forces that affect the allocation of failed banks to potential acquirers: the distance of a potential acquirer from the failed bank, the similarity of the business of a potential acquirer to that of the failed bank, and the capitalization of the potential acquirer. We show that these forces are also related to the losses the FDIC realized from bank failures. We conclude by interpreting these facts within the fire sales setting of Shleifer and Vishny (1992).

The first fact we document is that local banks are by far the most likely acquirers of failed banks. We find striking results: only about 15 percent of failed banks are sold to a bank that does not currently have branches within the same state, and more than one-third of failed banks are sold to a bank that has at least one branch in the same zip code. Formally stated, we find that a geographically proximate bank is significantly more likely to acquire a failed bank. This result is robust to the inclusion of failed bank fixed effects and potential acquirer/quarter fixed effects. This implies that this effect is identified not by the inherent quality of the failed bank or of the acquirer, but rather by the relative distance between the failed banks' and acquirers' branch networks. Consistent with the idea that soft information deteriorates with geographic distance, we find that in regions with more soft information, acquisitions of failed banks by local banks are more likely. Our evidence is not consistent with the idea that information technology and the integration in banking markets have allowed geographically distant banks to acquire failed banks (Cochrane, 2013).

[1] State chartered banks, which constitute 65% of failed banks in our sample, received approximately $50 billion of TARP funds to help them absorb liquidity shortfalls during the financial crisis.

We also uncover a second force that affects the allocation of failed banks to potential acquirers: differences in banks' specializations. Some failed banks focus more on consumer lending, others on mortgages, still others on commercial loans. We find that failed banks are significantly more likely to be sold to potential acquirers whose portfolios of loans have a similar composition, whether on the dimension of residential real estate loans, commercial and industrial loans, consumer loans, or commercial real estate (CRE) loans. Banks also differ in the services they offer, with some banks providing insurance and brokerage services while other banks do not. A failed bank is more likely to be acquired by a bank that offers similar services. Failed bank and acquirer/quarter fixed effects ensure that these results are not driven by inherent characteristics of the failed bank or potential acquirer; rather, it is the relative similarity between the portfolio composition and services offered by potential acquirers and a given failed bank that explains who is most likely to acquire it. The effects we document are economically meaningful. For instance, the likelihood of acquisition declines by a third of the mean if a potential acquirer's CRE portfolio share distance from the failed bank differs by one standard deviation.

The third force that affects who acquires a failed bank is the capitalization of potential acquirers. We draw on the insight from Shleifer and Vishny (1992) that in auctions of distressed assets potential buyers may be distressed as well, and therefore unable to purchase the assets. We show a monotonic relationship between the capitalization of potential local acquirers and their propensity to acquire failed banks: the 20% best capitalized local buyers acquire over 30% of failed banks, while the 20% worst capitalized local buyers acquire only 10% of failed banks.

Next we examine how these forces interact with each other to affect the allocation of failed banks. We want to understand whether capitalization of potential acquirers affects how failed banks are allocated along the dimension of distance and business similarity. The notion is that even though local banks are the most likely acquirers of a failed bank, they may not be able to take advantage of their higher valuations if they are distressed. Failed banks would then be sold to distant banks that are better capitalized even if distant banks value the failed banks less. Similarly, low capitalization of potential acquirers in related businesses may prevent the sale of the failed bank to these otherwise likely acquirers.

Consider local potential acquirers, defined as being within 100 miles of the failed bank. If their capitalization is at the median, the probability of acquisition declines with distance approximately 35% faster than if the capitalization of local bidders is one standard deviation below the median. Similarly, local potential acquirers in related lines of business are most likely to acquire a failed bank if they are well capitalized. However, low capitalization of these buyers forces the sale of a failed bank to acquirers that are in less related lines of business. As before, we obtain these results after accounting for failed bank and acquirer/quarter fixed effects, implying that these results are not driven by inherent failed bank or potential acquirer characteristics. Overall, these results suggest that the three forces that affect the allocation of failed banks interact in a meaningful way.

There are two broad channels that can explain the results on failed bank allocation. Under the first alternative, failed bank allocation is driven by choices of potential acquirers: a bank acquires a failed bank because it chooses to bid more for the failed bank than other potential acquirers, which either bid less or choose not to participate in the bidding process. Under the second alternative, the FDIC chooses which banks are allowed to bid in an auction through its eligibility criteria, and it is these criteria that affect failed bank allocation. To separate these alternatives, we compile the list of actual bidders of each failed bank in our sample. We show that our results persist even when we constrain our sample to the actual acquirers that have been approved by the FDIC and thus satisfy the eligibility criteria. Therefore, our results are unlikely to be driven by FDIC eligibility criteria. We reach the same conclusion when we directly impose FDIC criteria on the set of potential acquirers in our sample.

The sale of failed banks results in substantial costs to the FDIC. We show that the costs to the FDIC depend on the *composition* of potential acquirers for a failed bank, and that this composition is related to the forces we describe above. The results described above suggest that potential acquirers located close to the failed bank and that are in similar lines of business are most likely to purchase a failed bank, if they are well capitalized. If their capitalization is low, on the other hand, then the failed bank has to be sold to another bank, which presumably values the failed bank less. We show that lower capitalization of potential acquirers best suited to purchase a failed bank results in significantly higher cost of resolution for the FDIC. The 20% of failed banks with the highest share of well-capitalized local bidders have resolution costs of approximately 25% of assets. For the lowest quintile, the costs are over 33% of assets. This is a large change relative to a standard deviation of resolution costs of 12%. We show that these results are also robust to accounting for fixed effects of the quarter and the state where the failed bank is located, which implies that macroeconomic conditions and regional characteristics of the failed bank do not drive our findings.

One possible concern with the last set of results is that the capitalization of local acquirers may be low because they were exposed to the same negative local shock as the failed bank. The capitalization of local potential acquirers could then proxy for the severity of regional shocks that impact the failed bank. Such a correlated shock would cause both higher costs to the FDIC and low capitalization of local potential buyers. We address this concern by exploiting variation in capitalization of local buyers that is plausibly exogenous to the regional economic environment of the failed bank. Because different parts of the U.S. were exposed to different price declines after 2006, we establish that the geographic portfolio of a bank influences the losses a bank suffers in the aftermath. We then exploit losses that potential acquirers incur due to house price drops in regions outside the failed bank's operational area to instrument for the capitalization of local acquirers. Since we focus only on losses incurred outside the region of the failed bank, these losses are by construction unrelated to local economic conditions. The instrumental variable results confirm our findings. Last, we provide several tests to ensure our results are robust to alternative ways of measuring FDIC resolution costs, and to heterogeneity in bid characteristics.

We interpret the facts we document within the fire sales setting of Shleifer and Vishny (1992). Our first set of results shows that potential acquirers that are located close to a failed bank, and that are in similar lines of business, are most likely to purchase it. These acquirers are best suited to acquire a failed bank from the perspective of its assets. However, if the capitalization of these acquirers is low, then the bank is sold to an acquirer that is more distant, and whose business lines are less similar, but that is better capitalized. The latter values the bank less, so the failed bank is not allocated to the best user. By relating these forces to costs of the resolution, we are able to quantify the costs of fire sales to the FDIC. Therefore, in addition to sources of FDIC costs, which have been measured in the literature (James, 1991), we find fire sales to be a substantial component of FDIC costs.

Our results are relevant to the current policy debate of whether and how to support the banking system after negative shocks. Supporting the banking system is broadly based on the notion that a bank is special, and its ability to lend is embodied in its collection of assets and clients' relationships with its employees, which may not be easily or quickly replaced. Opponents argue that even if a particular bank is not easily replaced, failed banks can be sold efficiently and swiftly to a large pool of available banks in the system. Therefore bank support is not needed. The argument rests on the premise that deregulation and information technology have made selling banks efficient. Our facts suggest that fire sales of failed banks misallocate bank assets and employees, and provide an opportunity to measure some of these costs. Therefore, policymakers have to weigh the costs of fire sales against costs of supporting banks outright.

Our paper is related to several strands of literature. First, it is most directly related to the bank failures literature. The literature has mostly studied the S&L crisis (James and Wier, 1987; James, 1991) with a focus on the characteristics of the failed banks or the method the FDIC uses to dispose them. We focus on the allocation of the failed bank to potential acquirers, exploring the match between the failed bank and the potential acquirer as a key determinant of failed bank allocation and the losses borne by the FDIC. Our facts speak to the literature that examines whether government should bail out failed banks when the best users of assets are liquidity constrained (Acharya and Yorulmazer, 2008; Acharya, Shin and Yorulmazer, 2010).

We also contribute to the literature on relationship banking and the importance of soft information in loan production. The literature suggests that relationships add value because banks have information about borrowers (e.g., Diamond, 1984; James, 1987). The literature also argues that relationships increase the availability of credit and reduce interest rates on loans, especially for small firms (e.g., Berger and Udell, 1995; Petersen and Rajan, 2002). Other work suggests that deregulation and technological change brought significant changes in the banking system (e.g., Kroszner and Strahan, 1999), but small banks may be able to maintain the advantages they gain from relationship banking in the wake of these changes (e.g., Berger et al., 1998; Berger et al., 2005). A related recent strand of literature has argued that despite significant improvements in financial innovation over the past few years, such as securitization, the location of the branch network still matters for a bank's investment decisions (Gilje, Loutskina and Strahan, 2013). Our paper contributes to this work by arguing that these dimensions play a critical role in the allocation of failed banks: the information embedded in relationships is still relevant and must be taken into account when analyzing the effects of bank mergers or failures.

The rest of the paper is organized as follows: In Section II we discuss the institutional background. In Section III we present our data sources. Section IV provides descriptive statistics. Sections V and VI outline the main empirical results. Section VII discusses our findings in the context of the Shleifer and Vishny (1992) framework, and Section VIII concludes.

II. Institutional Background

Federal and state banking regulators regularly monitor the financial condition of depository institutions to limit the risks of individual bank failures. If the banking institution becomes critically undercapitalized, the primary regulator of the depository institution will initiate the resolution activities by sending a failing bank letter to the FDIC.[2] The FDIC contacts the management of the failing depository institution and engages a third-party financial advisor to compile initial information and perform an asset valuation review. The financial advisor identifies a sample of assets and estimates a loss factor in each asset category. The FDIC uses these estimates to set the reservation value on the subsequent sale of the assets of the depository institution, and chooses the resolution structure.

During the recent financial crisis, the FDIC chose the Purchase and Assumption (P&A) transaction as the resolution method in the great majority of receivership cases (roughly 95%). Accordingly, we will focus on such transactions in our analysis. In a P&A transaction, the FDIC uses a process that resembles a first-price sealed bid auction to sell some or all of the assets and liabilities of the depository institution. The FDIC will opt for another resolution method only

[2] Under FDIC regulations, a depository institution is critically undercapitalized if its ratio of tangible equity to total assets is equal to or less than 2.0%.

when the auction does not generate any bidding interest or when the highest bid is below the FDIC's reservation value.

After the FDIC gathers financial information and chooses a resolution method, it starts marketing the failed depository institution to a pool of potential buyers that had previously expressed their interest in bidding for failed institutions. To receive regulatory approval to bid in a P&A transaction, the potential bidder must be a chartered financial institution or an investor group that has received a conditional charter or is in the process of obtaining a "de novo" charter. Moreover, the financial institution must be well capitalized and possess a CAMELS rating of 1 or 2, a satisfactory Community Reinvestment Act (CRA) rating, and a satisfactory anti-money-laundering record.

The FDIC provides all approved bidders with information about the failed institution. The information package contains loan reviews, schedules representing the value of the items on the failed bank's balance sheet, and operational information. Potential bidders have the opportunity to review the individual loan documents as part of their on-site due diligence. Industry documents suggest that the due diligence period is merely four to six days for a team of six to eight people, which is severely compressed relative to a typical merger and acquisition.

The bidding generally starts twelve to fifteen days before the scheduled closing of the failed bank. The bidders can place one or more sealed bids for the failed bank. The Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991 mandates the FDIC to choose the bid that is least costly to the Deposit Insurance Fund (DIF). To meet this requirement, the FDIC evaluates all submitted bids using its proprietary least-cost test model and selects the bid whose terms entail the least estimated cost for the DIF if those costs are below the reservation value set by the FDIC.

When a failing depository institution enters receivership, the claims of the insured depositors are transferred to the FDIC, which is subrogated to the claims of depositors. The FDIC subrogated claim has a first lien on the proceeds of the receivership. The DIF took a loss on most bank failures that occurred during the recent financial crisis, suggesting that the receivership proceeds do not cover the FDIC's subrogated claim and that the FDIC is the residual claimant in most receiverships (Hynes and Walt, 2010). Since the beginning of 2008, the DIF lost approximately $90 billion due to depository institution failures. The fund reached a negative balance during the third quarter of 2009 but has since recovered and stood at $33 billion as of December 31, 2012, which corresponded to 0.45% of the total insured deposits in the system (Davison and Carreon, 2010). The FDIC answered to the large losses on its DIF by raising deposit insurance premiums and collecting a special assessment of 5 basis points on all depository institutions.

III. Data and Key Variables

We obtain data with the terms and characteristics of each government-assisted deal from SNL Financial. The dataset contains information on the resolution method used for each failed bank. From 2007 to 2013, the FDIC acted as receiver for 492 commercial and savings banks and used the P&A transaction as the resolution method in 467 receiverships.[3] In the remaining 25 cases, there were either no interested bidders or the bids fell below the FDIC's reservation value, and consequently the FDIC opted for liquidating the estate of the failed bank and paying off the insured depositors. We exclude these cases because there is no data on cost of resolution that is available.

As stated above, the FDICIA mandates the FDIC to choose the least costly option to the DIF. To comply with that mandate, the FDIC estimates the cost of each bid for the failed bank using a proprietary algorithm, and selects the bid with the lowest estimated cost. The estimated cost of resolution associated with each P&A transaction is disclosed by the FDIC and is also available in the SNL Financial database.

We obtain the financial characteristics of failed banks, all other commercial banks, and savings banks operating in the United States from the quarterly Reports of Condition and Income that banks file with the FDIC, and obtain financial information on savings banks prior to 2012 from SNL Financial. These regulatory reports provide detailed information on the size, capital structure, and asset composition of each commercial and savings bank. To construct the primary sample we exclude from the analysis (i) six P&A deals in which the FDIC marketed several bank subsidiaries of a single holding company in the same resolution process; (ii) the government-assisted deals involving Washington Mutual Bank and the IndyMac Federal Savings Bank, because their complexity required a special resolution method involving direct negotiation with the interested bidders; and (iii) the resolution process of the Independent Bankers' Bank of Springfield, which required the creation of a bridge bank that was later sold to another Bankers' Bank specializing in providing correspondent services to its client banks.

Bank location data for each commercial and savings bank come from the Summary of Deposits (SOD) database provided by the FDIC. This database contains information on the geographical coordinates, location, and deposits of each branch of every commercial and savings bank operating in the United States. We complement the SOD dataset by assigning latitudes and longitudes to each branch address whenever geographical coordinate data are missing. We geocode branch addresses into coordinates via Google Geocoding. We compute measures of geographical distance between the branch networks of each failed bank and all other commercial

[3] We restrict our analysis to this period since we do not have detailed data on transactions prior to 2007. Note, however, that the transactions before this period correspond to a tiny fraction relative to those observed in the post-2007 period.

and savings banks operating the United States in the year prior to the bank failure. We calculate geographical distance between banks using two metrics. First, we construct a variable that captures the average geodetic distance between all branch pairs. Second, we create a set of indicator variables that take the value of 1 if a commercial or savings bank has at least one branch in the same zip code as any of the branches of the failed bank. We also compute the indicator at the county and state level.

IV. Descriptive Statistics

The period from 2007 to 2013, which we study, saw an unprecedented number of banks being taken into receivership by the FDIC and then sold at auctions. This fact can be clearly seen in Figure 1, which shows the number of bank failures from 1994 onward. From 1994 to 2006 the average annual number of bank failures is five, and does not exceed fifteen. In contrast, 2010 saw a peak of bank failures at 157.

These bank failures impose substantial costs on the FDIC. Figure 2A shows the distribution of resolution costs and the size of failed banks that were sold during our sample. The median failed bank's assets are $211 million, with a significant dispersion (standard deviation of $2 billion). Similarly, the costs of resolution in the sample are relatively large, with a median of $55 million and standard deviation of $765 million. Figure 2B shows that resolution costs are sizable relative to the assets of the failed bank: the median resolution cost from 2007 to 2013 was 28% of total assets of the failed bank.

Table 1 presents descriptive statistics of key variables used in our analysis for failed banks (Panel A), their acquirers (Panel B), and their potential acquirers, i.e. banks that did not fail (Panel C) over the sample period. Failed banks tend to be smaller, experience higher losses on their loan portfolio, and have worse financial health relative to acquirers or potential acquirers. All banks tilt their lending to real estate, which constitutes more than 60% of their asset portfolio. These patterns also emerge if we stratify the sample yearly rather than pooling the sample. Relative to other banks, eventual acquirers tend to be larger and have a slightly larger residential and commercial real estate tilt in their loan composition.

Most interestingly, acquiring banks tend to be located closer to failed banks relative to other potential acquirers. The average distance between the eventual acquirer and a failed bank is 200 miles, rather than 900 miles for other potential acquirers. The loan portfolios of eventual acquirers are also more similar to those of the failed bank than are portfolios of other potential acquirers. The average share of CRE loans for an eventual acquirer differs from that of the failed bank it acquired by 18 percentage points (pp). For potential acquirers, this difference is 35 pp.

These patterns will be fundamental to the facts that we will robustly establish in our main analysis.

We also note some additional key statistics of failed banks and eventual acquirers in our sample. At the time of the failure, failed banks assets average $759 million, with a standard deviation of $2.441 billion. These banks are largely state chartered (65%), and 5% are part of a bank holding company holding more than one commercial and savings bank. The assets of acquirers in the sample average $11.275 billion; 55% of acquirers are state chartered and 26% are organized as a multibank holding company.

In Table 2 we formally present some of these same inferences by estimating a logit of the event that a potential acquirer acquires a failed bank as a function of the financial and asset characteristics of the potential acquirer. For notational simplicity we use $\Phi(.)$ to denote a logit and estimate the following specification:

$$\Pr\left(y_{ijt}=1\right)=\Phi\left(\alpha+\Gamma_i X_{it}+\Gamma_j X_{jt}+\mu_t+\varepsilon_{ijt}\right),$$

in which *i* indexes a failed bank at time *t*, and *j* indexes a potential acquirer. The dependent variable y_{ijt} is a dummy variable, with 1 indicating that potential bidder *j* acquired failed bank *i* at time *t*, and 0 if not. We account for characteristics of failed banks by including a plethora of failed bank characteristics, X_{it}, and potential acquirer characteristic , X_{jt}, as discussed in notes to Table 2. We also include quarter fixed effects, μ_t, to account for any macro movements. The results from this analysis mirror the descriptive statics in Table 1 (Panels B and C). The probability that a given potential acquirer acquires a failed bank is correlated with acquirer's characteristics in an economically meaningful way. For instance, a standard deviation increase in the Tier 1 Capital Ratio of the potential acquirer increases the likelihood of acquisition by 7.6 pp, evaluated at the mean values of other variables.[4]

V. Failed Bank Acquisition

V.A The Role of Distance

V.A.1 Are Failed Banks Sold Nonlocally?

[4] Similarly, the marginal effects of the Leverage Ratio and % Core Deposits variables are also economically large. Evaluated at mean values of other variables, a standard deviation increase in Leverage Ratio and % Core Deposits raises the likelihood of acquisition by 1.5 and 2.9 pp, respectively.

We begin our main analysis by asking whether geographic proximity of a potential acquirer to the failed bank increases the probability of an acquisition. One could imagine that the proximity of the potential acquirer does not play a role. As Cochrane (2013) contends, failed banks could be "swiftly bought up by other banks even out of state."

A simple cut of the raw data in Figure 3 suggests that failed banks are rarely sold to distant banks. In Figure 3A we sort potential acquirers into 20 bins, which contain an equal number of potential acquirers, sorted by the average distance of their branch networks to that of the failed bank. More than 60% of failed banks during the sample period are acquired by the 5% of potential acquirers that are located closest to the failed bank. The distance of the branch networks of these potential acquirers from the branch network of the failed bank is less than 196 miles. The results are also striking if we restrict the sample to the 5% of closest potential acquirers, as in Figure 3B. The potential acquirers with an average branch network distance of less than 21 miles, which represent the 0.25% closest potential acquirers, acquire over 12% of failed banks. The patterns are similar when we use an alternative metric of distance in Appendix Figure A.1. These figures clearly show that most failed banks are sold very locally, and that the share of banks sold declines quickly with distance.

We formalize this insight by building on the specification from Table 2. We estimate a conditional (fixed effect) logit specification; for notational simplicity we use $\Phi\left(.,\mu_{it}\right)$ to denote a fixed effect logit with a μ_{it} fixed effect:

$$\Pr\left(y_{ijt}=1\right)=\Phi\left(\alpha+\Gamma X_{jt}+\beta_1 d_{ijt},\mu_{it}\right),$$

in which *i* indexes a failed bank being auctioned at time *t*, and *j* indexes a potential acquirer. The dependent variable y_{ijt} is a dummy variable, with 1 indicating that potential bidder *j* acquired failed bank *i* at time *t*, and 0 if not. The dependent variable of interest is d_{ijt}, which measures the average distance of the branch network of the potential acquirer from the branch network of the failed bank. We control for characteristics of a potential acquirer, such as its asset size, composition of loans, and capitalization in X_{jt}.

In the specification we also condition on failed bank fixed effects μ_{it}. We do so to ensure that our results are driven by the distance between the failed bank and the acquirer, not the characteristics of the bank being sold. One concern could be that failed banks that are far away from potential acquirers also have worse assets, or assets that are very specific. Alternatively, states' regulation or regulators may affect which types of banks are located in a given state (see Agarwal et al. 2014), as well as the distance to potential acquirers. Failed bank fixed effects μ_{it}

control for these alternatives. Moreover, failed bank fixed effects subsume any time variation, such as aggregate trends in bank sales, since the failure happens at one point in time, as well as between-state variation. The variation in our estimates therefore comes from within failed bank differences in geographic proximity of potential acquirers to the failed bank. We cluster the standard errors at the level of the failed bank's state headquarters.

Table 3A presents the results and confirms the intuition from Figure 3. The coefficient on distance, β_1, is negative and statistically significant. Potential acquirers that are located farther from a failed bank have a lower probability of acquiring it. This estimate is economically meaningful. The average marginal effect of a 100-mile increase in the distance between the failed bank's and potential acquirer's branch networks is to reduce the expected probability of acquisition by 3 pp. The effect of distance is stronger conditional on being located close to the failed bank: a 100-mile increase in distance reduces the likelihood of acquisition by 13.6 pp for potential acquirers within 100 miles of the failed bank, but only 0.25 pp for potential acquirers 1,000 miles away from the failed bank.

Next, we perform a serious of robustness checks to further confirm that failed banks are sold very locally. To better understand the effect of distance, we restrict our subsample to acquirers whose branches are within a 200-mile radius. In unreported tests we find that the effect of distance persists when we restrict ourselves to the subsample of these more plausible potential acquirers. To ensure that our results are not driven by unobserved characteristics of potential acquirers, we include acquirer/quarter fixed effects μ_{jt} and estimate the following specification:

$$\Pr\left(y_{ijt}=1\right)=\Phi\left(\alpha+\mu_{jt}+\beta_1 d_{ijt},\mu_{it}\right).$$

All failed bank and acquirer factors are subsumed in fixed effects. The remaining variation we exploit is the interaction between the characteristics of the potential acquirer and the failed bank and the relative distance between them. Because of the acquirer/quarter fixed effects, the sample of potential acquirers in these conditional logit tests is limited to banks that acquired a failed bank in the same quarter in which that failure occurred. In spite of this very limited sample, our results in columns 2 and 3 are quantitatively and qualitatively similar to the baseline estimates.

Because banks had substantial exposures to the real estate sector, we explore how house price dynamics faced by the failed bank shape the effect of distance (see Keys et al., 2012). In Table 3B we stratify the sample based on whether the failed bank is in a coastal area, which experienced larger boom-bust house price cycles during the last decade. Alternatively, we stratify directly based on house price growth experienced in the failed bank region. The results presented in columns 1 to 4 show that in each of these subsamples, distant banks have a lower probability of purchasing a failed bank. The estimated coefficients also suggest that the effect of distance is slightly less pronounced if failed banks are located in coastal states or operating in areas that had experienced high house price growth between 2001 and 2006. For instance, a 100-mile increase in distance reduces the likelihood of acquisition by 2.6 and 3.1 pp in coastal and noncoastal states, respectively. Similarly, a 100-mile increase in distance reduces the likelihood of acquisition by 2.3 and 3.5 pp for failed banks located in areas with high and low house price growth, respectively. In Table 3C we assess whether these effects vary based on failed banks' specialization. We stratify failed banks based on the percentage of CRE, Residential, and C&I loans held by the failed bank. The results of Table 3C show that the effects of distance are present across all subsamples, although the sales are most local for failed banks with a low share of CRE loans.

There are several potential reasons why failed banks sales are local. A large literature has studied how the transmission of soft information within banks deteriorates with geographic distance (Stein, 2002; Petersen and Rajan, 2002). A distant potential acquirer will not be able to operate the acquired failed bank very efficiently because of the loss in soft information. Nearby banks might also be better able to exploit economies of scale, such as lower overhead, easier servicing of branches and joint ATMs, or greater market power (Akkus, Cookson, and Hortacsu, 2014). Next we explore the conjecture that the effect of distance in failed bank acquisitions is related to soft information loss.

V.A.2 Does Distance Reflect Soft Information?

If soft information deteriorates with distance, an acquisition by a local bank would be especially valuable in the sale of failed banks with an important soft information component. Because banks in our sample had substantial exposures to the real estate sector, we exploit variation in the amount of soft information about real estate values. We do so by measuring the quality of hard information contained in public tax assessments of real estate values following Garmaise and Moskowitz (2004).

Property tax authorities periodically evaluate the quality of property assessments in their jurisdictions. The most popular measure of assessment quality is the coefficient of dispersion used by Garmaise and Moskowitz (2004). The central input is the ratio between the market value of properties recently sold and their assessed value, which is frequently determined by statute. Suppose that the assessed value is legislated at 33% of market value. If assessments measure market values perfectly, then the ratios of assessed values to market value are the same for all assessed properties, 33%. Outside investors can then rely on the hard information collected by the tax authorities to closely track the market value of a property. Consider the opposite situation in which the ratios are dispersed—some assessed values are 10% of the actual value, others are 50%. Then the assessed values provide little information to outside investors. The coefficient of dispersion (COD) formally measures how dispersed the ratios are.[5] When public assessments are less accurate, the measure is larger and investors have to rely on soft information about local real estate market conditions rather than public assessments.

We exploit this measure to examine whether local banks are more likely to acquire a failed bank in areas with more soft information, using the following specification:

$$\Pr\left(y_{ijt}=1\right)=\Phi\left(\alpha+\mu_{jt}+\beta_1 d_{ijt}+\beta_2 d_{ijt}COD_{ij},\mu_{it}\right),$$

in which COD_{ij} represents the coefficient of dispersion, our measure of the importance of soft information in the real estate market. The level effect of COD_{ij} is absorbed by the failed bank fixed effect μ_{it}. Our independent variable of interest is the interaction between the distance of potential acquirers and the amount of soft information in the local market, $d_{ij}COD_{ij}$, with the corresponding coefficient of interest β_2. As in other specifications, we also include acquirer/quarter fixed effects μ_{jt} and cluster the standard errors at the level of the failed bank's state headquarters.

The results are presented in Table 4. In column 1 we use a dummy variable to capture the degree of soft information in a failed bank's portfolio. Specifically, we use an indicator that takes a value of 1 if the failed bank is in an above-median COD area *(High COD)* and 0 otherwise. The coefficient on distance β_1 is negative and statistically significant, which indicates that distant potential acquirers are less likely to acquire failed banks even in markets with less soft information. More importantly, as the interaction term reveals, local soft information significantly increases the advantage of local banks. If we compare areas with above-median soft information to those below median, we find that the coefficient of distance increases over 50 percent. For potential acquirers within 100 miles of the failed bank, a 100-mile increase in distance reduces the likelihood of acquisition by 17.6 pp in high-COD areas, whereas the same increase in low-COD areas reduces the likelihood of acquisition by just 11.4 pp. The incremental effect of COD on the marginal effect of distance rapidly disappears as we move farther away from the failed bank. For potential acquirers within 300 miles from the failed bank, a 100-mile increase in distance reduces the likelihood of acquisition by 7.4 pp in high-COD areas, whereas the same increase in low-COD areas reduces the likelihood of acquisition by 6.5 pp. We obtain similar inferences when we use a continuous measure of COD in column 2 instead.

[5] The coefficient of dispersion is calculated as $COD=\frac{\frac{1}{N}\sum_i^N|R_i-R^{med}|}{R^{med}}\times 100$, where R_i is the assessment-to-market ratio for the i^{th} property sold, R^{med} is the median of the assessment-to-market ratio of the sold properties, and N is the number of properties sold.

Garmaise and Moskowitz (2004) make a strong case that COD measures plausibly exogenous variation in soft information.[6] Even if that were not the case, the variation we use to identify our effect is based on the interaction between COD and distance between a bank and a potential acquirer. Because we include both failed bank and acquirer/quarter fixed effects these results are not driven by the fact that banks or potential acquirers are different in areas of high rather than low COD. To generate our results, areas with high administrative mismeasurement would be areas in which local banks are a *relatively* better match for the failed bank in that area and a relatively worse match for distant failed banks on dimensions that are not related to distance or soft information. In areas with little administrative mismeasurement, the result would be reversed. We think this alternative, while possible, may be unlikely.

We also use alternative measures of soft information. Following Granja (2013) and Agarwal et al. (2014), we measure whether the failed bank was publicly traded before failure and whether the failed bank is large relative to the sample of failed banks. The idea behind these proxies is that public information is more readily available for these banks. Therefore soft and local information play a larger role in acquiring private and smaller banks, which should provide an advantage to local potential acquirers. We confirm this conjecture in columns 3 and 4 of Table 4.

Overall, these results paint a clear picture. Failed banks are generally acquired by very local banks and are rarely sold out of state. This effect is robust to failed bank and potential acquirer fixed effects, and is present across regions that saw different housing boom-bust cycles over the last decade as well as among failed banks with different specializations. These effects are exacerbated for banks in areas with more soft information. These results suggest that the valuations of potential acquirers differ, with local banks valuing failed banks more, especially in areas with pervasive soft information.

V.B The Role of Asset Specificity

In Section V.A.1, we showed that geographic proximity of a potential acquirer to the failed bank increases the probability of an acquisition. Next, we examine whether asset specificity affects the allocation of failed banks to potential acquirers. Some failed banks focus more on consumer lending, others on mortgages, still others on commercial loans. Banks also differ in the services they offer, with some banks providing insurance and brokerage services while other banks do not. Given that banks specialize in different types of loans, their assets and human capital are likely specialized as well. It is possible that the potential acquirer best suited to deploy these assets is specialized in a similar way.

[6] They control for the level of heterogeneity in local properties and the house price growth rate in the region. The authors also find that property age and COD have a strong positive correlation, which allays concerns of selective offering of properties with shorter income histories in regions with high COD.

There are substantial differences in the portfolio composition of failed banks. The average failed bank's portfolio comprises 58% CRE loans, but there are large differences between failed banks, with a 20 pp standard deviation. For residential loans the mean is 24% and standard deviation is 18 pp (Table 1). As mentioned earlier, these substantial differences in portfolios are not unusual and are also observed in the potential bidders and actual acquirers.

One simple way to examine whether failed banks are more likely to be acquired by banks with similar portfolios is to compute the correlation between the portfolios of the failed bank and the acquirer. The correlation between the share of CRE loans of acquirers and failed banks is 0.295, which shows that failed banks are sold to acquirers with similar portfolios. This relationship can also be seen in Figure 4A: we sort potential acquirers on their portfolio distance from the failed bank and group them into quintiles. We then plot the share of failed banks (as a percentage of total failed banks in our sample) that were acquired by potential acquirers in different quintiles for the CRE portfolio distance metric. Approximately 33% of failed banks are acquired by the 20% of potential acquirers with the most similar share of CRE loans in their portfolio. Conversely, fewer than 5% of failed banks are acquired by the 20% of potential acquirers whose CRE portfolio shares are most dissimilar. A parallel pattern is presented in Figure 4B when we sort potential acquirers by their residential loan portfolio share. These simple cuts of raw data suggest that failed banks are acquired by banks with similar portfolios. The results with other portfolio metrics are similar, though substantially weaker. This is reasonable: as mentioned earlier, most banks in our sample have their asset holdings in commercial and residential real estate.

We formally examine whether similarity to the failed bank increases the probability of acquisition building on the conditional logit specification from above:

$$\Pr\left(y_{ijt}=1\right)=\Phi\left(\alpha+\mu_{jt}+\beta_1 \, portfolio\, distance_{ijt}+\beta_2 d_{ijt}, \mu_{it}\right),$$

in which y_{ijt} is a dummy variable, with 1 indicating that potential bidder *j* acquired failed bank *i* at time *t*, and 0 if not. The independent variable of interest is $portfolio\, distance_{ijt}$, which measures the absolute difference in the loan portfolio composition between the failed bank and a potential acquirer. For example, in the first specification $portfolio\, distance_{ijt}$ measures the absolute difference between the portfolio shares of residential mortgages. As before, we control for the failed bank fixed effect μ_{it} and the potential acquirer/quarter fixed effect μ_{jt}. Therefore our results are not driven by portfolio composition of failed banks or potential acquirers but the interaction of the two. We also directly control for geographic distance, d_{ijt}, to make sure our results are not driven by the correlation between business similarity and geographic proximity. We cluster the standard errors at the level of the failed bank's state headquarters.

Table 5A presents the results. We measure the distance in portfolios using five different specifications. We compute the absolute difference in the share of residential, commercial and industrial, consumer, and CRE loans. We test different measures of asset specificity first individually and then simultaneously. All coefficients are negative, suggesting that potential acquirers whose portfolio composition differs from the failed bank are less likely to acquire the failed bank. Because banks are likely similar on several portfolio dimensions simultaneously, it is difficult to separately identify the effects of different portfolio categories; i.e., the measures are nearly multi-collinear. The last specification shows that, while the signs on all the portfolio distance metrics are maintained when the measures are included simultaneously, the only statistically significant coefficient is on CRE loans. Accordingly, we will focus on CRE loans as the metric of portfolio distance in our analysis.

These effects are also economically large: a one-standard-deviation increase in the absolute difference between the residential loan portfolio shares of potential acquirers and failed banks reduces the likelihood of acquisition by 8.8 pp, whereas a one-standard-deviation increase in the absolute difference of CRE loan portfolio shares reduces the expected probability of acquisition by 9.7 pp. Not surprisingly, given the large exposure of banks in our sample to real estate, the effect of a change in the portfolio distances of C&I or consumer loans is less important. A standard-deviation increase in the absolute difference between the C&I or consumer loan portfolio shares reduces the likelihood of acquisition by 6.4 and 2.6 pp, respectively, and the results are not statistically significant. These findings suggest that different dimensions of asset specificity play an important role in who acquires failed banks.

Next, we examine whether the similarity in financial services provided by the potential acquirer and the failed bank affects acquisition probabilities. Banks provide several different services, organized in fiduciary and custodian businesses and insurance, brokerage, and lease businesses. One would expect that a bank that has experience in insurance would be better able to manage a failed bank that also provides insurance services than would a potential acquirer with no insurance business. Therefore a potential acquirer's valuation of a failed bank should increase if they operate similar businesses in terms of financial services.

Table 5B presents the results in which we estimate the specification from above, but examine whether the potential acquirer and failed bank provide the same services. Again, the failed bank and potential acquirer fixed effects absorb the direct effect that providing services by the failed bank or a potential acquirer would have on the probability of acquisition. The coefficients are positive for all services when these are included separately as well as together, suggesting that if a failed bank provides a service, such as insurance, then a potential acquirer that provides the service is more likely to acquire it. These effects are economically meaningful. For instance, if both the failed bank and the potential acquirer offer insurance activities, the likelihood of acquisition increases by 4.1 pp, which is large compared with the conditional mean of 5%. Overall, the results of this section suggest asset specificity plays an important role in how failed banks are allocated.

V.C The Role of Capitalization of Potential Acquirers

The third force that may affect who acquires a failed bank is the capitalization of potential acquirers. We draw on the insight from Shleifer and Vishny (1992) that in auctions of distressed assets potential buyers may be distressed as well, and may therefore be unable to purchase the assets.

A simple cut of the raw data in Figure 5A suggests that capitalization of potential acquirers is an important factor in failed bank acquisitions. We sort local potential acquirers into quintiles according to their capitalization. The 20% best capitalized potential acquirers obtain over 30% of failed banks that go to local acquirers, while the 20% worst capitalized acquirers obtain 10% of failed banks. Next, we sharpen the analysis by restricting the sample to the most likely buyers: local potential acquirers that have the highest portfolio composition overlap with the failed bank based on CRE. We again sort potential acquirers into quintiles on capitalization and show the share of failed banks acquired for each quintile in Figure 5B. The potential acquirers in the best capitalized quintile acquire over 25% of failed banks in this sample, while the least capitalized quintile acquires approximately 9% of failed banks. These simple cuts of the data suggest that the capitalization of potential acquirers may play an important role in the allocation of failed banks.

We explore this question more formally by estimating the following conditional logit specification:

$$\Pr\left(y_{ijt}=1\right)=\Phi\left(\alpha+\beta_1 \text{capitalization}_{jt}+\Gamma X_{jt}+\beta_2\, portfolio\, dist_{ijt}+\beta_3 d_{ijt}, \mu_{it}\right),$$

in which $\text{capitalization}_{jt}$ measures the capitalization of a potential acquirer. The coefficient of interest β_1 measures the effect of potential acquirer capitalization on the probability of acquiring a failed bank. μ_{it} captures failed bank fixed effects, ensuring the estimate is not driven by the poor capitalization of the overall pool of interested acquirers for a given failed bank. X_{jt} controls for other characteristics of potential acquirers. We also condition on geographic distance and the portfolio distance between the potential acquirer and the failed bank to ensure that their correlation with capitalization is not driving the results. We cluster the standard errors at the level of the failed bank's state headquarters.

We present the results in Table 6. We measure potential acquirers' capitalization through either their *Tier 1 Capital Ratio* or their *Leverage Ratio*. As shown in columns 1 and 2, better capitalized potential acquirers according to either measure are more likely to acquire a failed bank. Since local banks are much more likely to acquire a failed bank, we re-estimate the specification focusing only on potential acquirers within 100 miles. In unreported tests we find that, even within the pool of local banks, it is the better capitalized banks that are more likely to acquire a failed bank.

V.D Interaction of Distance, Asset Specificity, and Capitalization

We have documented three distinct forces that affect the allocation of failed banks to potential acquirers: the distance of a potential acquirer to the failed bank, the relatedness of the business of a potential acquirer to that of the failed bank, and the capitalization of the potential acquirer. Next we examine how these forces interact with each other. We want to understand whether capitalization of potential acquirers affects how failed banks are allocated along dimensions of geographic distance and business similarity. The idea is that local banks are the most likely acquirers of a failed bank, but they may not be able to take advantage of their higher valuations if they are distressed. Failed banks would then be sold to distant banks that are better capitalized even if distant banks value the failed banks less. Similarly, low capitalization of potential acquirers in related businesses may prevent the sale of the failed bank to these otherwise likely acquirers.

We estimate whether in areas with less well-capitalized local acquirers failed banks are sold to relatively more distant potential acquirers. We estimate the following conditional logit specification:

$$\Pr\left(y_{ijt}=1\right)=\Phi\left(\alpha+\mu_{jt}+\beta_1 d_{ij}+\beta_2 d_{ij}\,local\ capitalization_{ijt},\mu_{it}\right),$$

in which $local\,capitalization_{ijt}$ measures the capitalization of local banks (potential acquirers). We include failed bank, μ_{it}, and potential acquirer/quarter, μ_{jt}, fixed effects. Therefore we study the effect that the capitalization of *other* local potential acquirers has on the effect of distance for a given potential acquirer. Note that the level of $local\,capitalization_{ij}$ is absorbed by the failed bank fixed effects, μ_{it}. Because the direct effect of distance between the failed bank and a potential acquirer, d_{ijt}, is not absorbed by the fixed effects, we control for it directly. Our coefficient of interest is β_2, the interaction between the capitalization of local banks and distance of the potential acquirer. We cluster the standard errors at the level of the failed bank's state headquarters.

We use two measures of local banks' capitalization: The first is the median capitalization of local potential acquirers, with local potential acquirers defined as banks whose branch network overlaps in at least one zip code with the branch network of the failed bank. The second is the share of local potential acquirers that are "well capitalized." We define a local potential acquirer as well capitalized if its Tier 1 capital ratio is above the median Tier 1 capital ratio of all potential local acquirers (across all failed banks in that quarter). The results are presented in columns 3 to 6 of Table 6. The results confirm that if local potential acquirers are poorly capitalized, distance to the failed bank is less of an impediment to acquiring it. This result is robust to different measures of local capitalization. Consider local potential acquirers, located within 100 miles of the failed bank. If their capitalization is at the median, the probability of acquisition declines with distance approximately 35% faster than if the capitalization of local bidders is one standard deviation below the median. These results are consistent with the idea that nonlocal banks are more likely to acquire a failed institution when local banks are poorly capitalized.

Capitalization of potential acquirers also affects the allocation of failed banks along the dimension of asset similarity. If potential acquirers whose asset portfolios are similar to those of the failed bank are distressed, they might not be able to take advantage of their higher valuations. Failed banks would then be sold to banks whose asset portfolios are not as similar. Results in Table 6 confirm that if potential acquirers with similar asset portfolios are poorly capitalized, then the failed bank is more likely to be sold to potential acquirers with less asset similarity.

Overall, these results suggest that the three forces that affect the allocation of failed banks interact in a meaningful way. Local potential acquirers in related lines of business are most likely to acquire a failed bank if they are well capitalized. However, low capitalization of these buyers forces the sale of a field bank to more distant acquirers that are in less related lines of business.

V.E What Drives Failed Bank Allocation? Bank Choices versus the FDIC's Eligibility Criteria

There are two broad channels that can explain our results. First, failed bank allocation is driven by the choices of potential acquirers: a bank acquires a failed bank because it chooses to bid more for the failed bank than other potential acquirers, which either bid less or choose not to participate in the bidding process. Alternatively, as we briefly describe in Section II, the FDIC chooses which banks are allowed to bid in an auction through its eligibility criteria, and it is these criteria that effectively determine failed bank allocation. Both alternatives are intriguing, and both may affect the allocation of failed banks. Nevertheless, we attempt to disentangle the two channels below, allowing for a cleaner interpretation of our results in Section VII.

The FDIC follows a two-step process: first, it restricts which bidders are eligible to bid in failed bank auctions; second, from the eligible bids it chooses the one that minimizes the cost of the failed bank resolution to the Deposit Insurance Fund. To be allowed to bid in a failed bank auction, a potential acquirer must have an adequate Community and Reinvestment Act (CRA) record, a CAMELS rating of 1 or 2, and a Federal Reserve Bank Holding Company (BHC) rating of 1 or 2. Its total assets must exceed two times the size of the failed bank if it is located in the same state, four times the size of the failed bank if it is located in a contiguous state, and five times the size of the failed bank if it is located in a nonadjacent state.[7]

To disentangle whether our results are driven by banks' choices or FDIC bidding eligibility criteria, we conduct two sets of tests. The first set of tests estimates our previous regressions on a sample in which we directly account for eligibility criteria imposed by the FDIC. The second set of results re-estimates our regression on a sample of actual bidders, whose eligibility is self-evident from their being allowed to bid.

The first set of tests start by re-estimating the main results on distance and asset specificity for the subset of potential acquirers that are eligible to bid according to the FDIC criteria described above. We present the results in Table 7.[8] In columns 1 and 2 we replicate specifications from Table 3 and Table 5, in which we control for failed bank and acquirer/quarter fixed effects. We explicitly impose the relative size criterion on the sample. We do not have information on CAMELS, CRA record, or the FED BHC rating of banks. Because we use acquirer/quarter fixed effects in a fixed effect logit, however, these regressions only use data from potential acquirers that have bid at least once in any given quarter. This implies that the institutions that are a part of these regressions must have CRA, CAMELS, and FED BHC ratings that satisfy the FDIC criteria in the quarter they were allowed to bid. In fact, any FDIC criteria that are acquirer-specific are accounted for by potential acquirer/quarter fixed effects. Note that the size eligibility criteria are relative to the size of the failed bank, and are therefore not absorbed and must be directly imposed. Imposing these criteria significantly decreases the number of observations of potential acquirers, from approximately 9,000 to approximately 5,000 observations. While noisier, the results in these two columns are very similar quantitatively to those in the unrestricted sample.

[7] For instance, see the website of the Texas Department of Banking: http://www.dob.texas.gov/banks-trust-companies/bidding-failing-bank.

[8] We find that there seems to be some discretion in how these rules are imposed by the FDIC. Approximately 25% of the winning bidders do not strictly meet the size criterion.

In the next column, we test the capitalization result for the sample of eligible bidders. As in Table 6, these regressions are not estimated with acquirer/quarter fixed effects. Again, even though the number of observations drops significantly, to 763,000 from 3 million, our results are similar: better capitalized banks are more likely to acquire a failed bank. In columns 4 and 5 we show that the results from Table 6, interacting local capitalization of potential acquirers and distance, also remain unchanged once we constrain ourselves to the sample of eligible potential acquirers.

In the second set of tests we constrain our sample to potential acquirers that we know were eligible to bid on a given failed bank—the actual bidders. We compile the list of actual bidders using information on the auction of each failed bank in our sample. Estimating the results on this sample eliminates concerns about FDIC eligibility since the sample now consists of potential acquirers that were allowed to bid by the FDIC. These specifications do not include potential acquirer/quarter fixed effects due to very few cases where the same acquirer bid for different targets in the same quarter. Even though the sample of potential acquirers is severely restricted and reduced to 943 observations, the results in columns 6–10 of Table 7 show that our inferences from earlier tables remain the same.

Restricting the results to actual bidders yields quantitatively very similar results to those in the unrestricted sample. The only exception is the effect of distance, which is substantially smaller among actual bidders relative to all potential acquirers. We already impose the FDIC distance criteria directly when we estimate the results in columns 1–5, and we find a large distance effect, similar to that of the unrestricted sample. This suggests that the decline in the effect of distance is not driven by FDIC criteria, but rather that far-off banks choose not to bid in the first place. Jointly, these results confirm that our previous results are robust to eligibility criteria imposed by the FDIC.

VI. FDIC Losses and Allocation Outcomes

As we describe in Section IV, there are substantial costs that the FDIC incurs in selling a failed bank, and these costs differ significantly across failed banks. We next explore the link between the forces that affect the allocation of failed banks and the costs of these sales to the FDIC.

Our previous analysis is at the level of the potential acquirer–failed bank pair, showing that potential acquirers are most likely to purchase a failed bank if they are located close to the failed bank, are in similar lines of business, and are well capitalized. Because banks are sold in auctions, our results imply that such potential acquirers are willing to pay the most for failed banks. The costs to the FDIC then might depend on the *composition* of potential acquirers for a failed bank, and how this composition is related to the forces we describe above. A simple cut of the data presented in Figure 6A suggests that there is a link between the capitalizations of the pool of local potential acquirers and the cost to the FDIC. For each bank we compute the share of well-capitalized potential acquirers and sort failed banks into quintiles according to this measure. The 20% of failed banks with the highest share of well-capitalized local potential acquirers have resolution costs of approximately 25% of assets. For the lowest quintile, the costs are over 33% of assets. This is a large change relative to a standard deviation of resolution costs of 12%. We obtain similar inferences if we sort banks based on the other capitalization ratio in Figure 6B. These simple plots suggest that the forces that affect the allocation of failed banks to potential acquirers have a substantial impact on FDIC losses.

As in Figure 6, we study the link between the capitalizations of the pool of local bidders and the cost to the FDIC, but we do so by estimating the following linear regressions:

$$\text{cost}_{its} = \alpha + \beta_1 local\,banks'\,capitalization_{its} + \mu_s + \mu_t + \Gamma X_{its} + \varepsilon_{its},$$

in which *i* indexes a bank, which failed at quarter *t* in state *s*. cost_{its} measures the estimated cost of resolution of the failed bank to the FDIC. $local\,banks'\,capitalization_{its}$ is the dependent variable of interest, which measures how well capitalized local potential acquirers are. Because aggregate conditions were highly correlated with the severity of banking failures, we control for the quarter in which the failed bank was sold, μ_t. State fixed effects μ_s control for differences in regulation and local conditions between the states in which banks fail, such as severity of the great recession or constraints faced by regulators which might lead to forbearance. X_{its} contains failed bank characteristics such as size, portfolio composition, and capitalization prior to failure. We cluster the standard errors at the level of the failed bank's state headquarters.

The results are presented in columns 1 and 2 of Table 8A. As in Section V.D we measure local banks' capitalization as the median capitalization of banks whose branch network overlaps in at least one zip code with the branch network of the failed bank, or by the share of local banks that are well capitalized. The results are robust to perturbations of these definitions. The magnitudes are also substantial. A one-standard-deviation increase in the median capitalization of local banks reduces the estimated cost of resolution by 2.3 pp of the assets of the failed bank. This represents approximately 19% of the standard deviation in the cost of resolution of failed banks.

The last four columns try to tighten the link between the forces that affect the allocation of failed banks and the costs to the FDIC. Potential acquirers located close to the failed bank that are in similar lines of business are most likely to purchase a failed bank, if they are well capitalized. If their capitalization is low, however, then the failed bank has to be sold to another bank, which presumably values the failed bank less. We test this conjecture in columns 3 and 4, measuring similarity based on the distance of CRE loan portfolios between the failed bank and potential local acquirers. A one-standard-deviation decrease in the median capitalization of the local acquirers with similar loan portfolios increases the costs of resolution by 1.15 pp, or almost 10% of the standard deviation. These effects are less pronounced but still relevant when we analyze difference in the portfolio shares of other loan types. These findings suggest that lower capitalization of potential acquirers best suited to purchase a failed bank results in a significantly higher cost of resolution for the FDIC.

In the previous section we also found that in areas with more soft information local banks have an advantage in acquiring a failed bank. We explore whether soft information is related to costs of resolution by estimating the following specification:

$$\mathrm{cost}_{its} = \alpha + \beta_1 COD_{ijs} + \mu_s + \mu_t + \Gamma X_{its} + \varepsilon_{its},$$

in which, as in section V.A.2, COD_{ijs} is the coefficient of dispersion that measures the amount of soft information in a market. We also proxy for soft information by considering whether the bank is publicly traded or not. The results in columns 5 and 6 suggest that, all else equal, a higher degree of soft information significantly exacerbates the cost of resolution. The cost of resolution of failed banks that are publicly traded is 3.74 pp lower than that of non-publicly-traded failed banks. This is in line with Granja (2013), who argues that the effect of being publicly traded partially stems from the greater information transparency of publicly traded banks. Moreover, bank failures in areas with little soft information (low COD) are 2.2 pp less costly. Our inferences survive in the last two columns when we include the capitalization variables along with the proxy for soft information.[9] Overall, the findings of this section suggest that the forces that affect the allocation of failed banks are also linked with substantial costs of failed bank sales to the FDIC.

VI.A Robustness to Regional Shocks

One possible concern with the last set of results is that the capitalization of local acquirers may be low because they were exposed to the same negative local shock as the failed bank. The capitalization of local potential acquirers could then proxy for the severity of regional shocks to the failed bank, lowering its value. Such a correlated shock would cause higher cost to the FDIC when local potential buyers are poorly capitalized. We already condition on state fixed effects in the specification above, so for such shocks to affect our results, they would have to be at a more local level, such as MSA.

[9] The findings are similar with COD as a proxy for soft information. We omit these results for brevity.

We address this concern by exploiting variation in capitalization of local buyers that is exogenous to the regional economic environment of the failed bank. Because regions of the U.S. were exposed to different house price declines after 2006, the geographic portfolio of a bank may influence the losses a bank suffered in the aftermath. We exploit losses that potential acquirers incur due to house price drops in regions outside the region of failed bank operations to instrument for the capitalization of local acquirers. This instrument likely satisfies the exclusion restriction by construction.

We first compute the exposure of each potential acquirer to house price declines outside of the regions in which the failed bank operates. For each potential acquirer–failed bank pair in our sample, we compute a house price index from the first quarter of 2006 to bank failure. We weigh the change in the MSA house price index[10] by the level of deposits of the potential acquirer in the same MSA. We do so only for regions that do not overlap with regions in which the failed bank operates. As before, consider failed bank *i* with branches in regions Ω_i, which fails at time *t*, and a potential acquirer *j* with branches in regions Ω_j and deposits per branch *r* of d_{jr}. Denote the MSA house price index of region *r* as p_{rt}. We construct the weighted price index as

$$\Delta p_{ijt} = \sum_{r \in \Omega_j - \Omega_i} \left(p_{rt} - p_{r2006} \right) \frac{d_{jr}}{\sum_{r \in \Omega_j - \Omega_i} d_{jr}} .$$

On average, the weighted house price index declines by 5% from 2006, which is consistent with the economic conditions faced by the U.S. since the financial crisis.

Define the change in the level of Tier 1 capital ratio of the potential acquirer since 2006 as $\Delta capitalization_{jt} = capitalization_{jt} - capitalization_{j2006}$. We study the impact of nonlocal changes in house prices for each potential acquirer–failed bank on this change:

$$\Delta capitalization_{jt} = \alpha + \beta_1 \Delta p_{ijt} + \mu_{it} + \Gamma X_{jt} + \varepsilon_{ijt}$$

We also include additional buyer characteristics and failed bank fixed effects in the first stage and cluster the standard errors at the level of the state where the failed bank's headquarter is located. Nonlocal house price declines are statistically significantly associated with the change in the level of Tier 1 capital ratio of the potential acquirer. The first-stage estimate is statistically significant (β_1=6.60 and *t*=17.5) and well above the conventional threshold of assessing the strength of the instrument (F=304). The estimate is also economically meaningful—a standard deviation decrease in the level of our weighted house-price index (16 bp) decreases the Tier 1 capital ratio by 105 bp. This is a large change relative to the median to 75th percentile difference in Tier 1 capital ratio of potential buyers of 4.5%.

[10] We use the Federal Housing Finance Agency quarterly MSA house price index.

Our nonlocal house price instrument generates variation in the capitalization of an individual potential acquirer. As in the baseline specification we measure local banks' capitalization as the median capitalization of banks whose branch network overlaps in at least one zip code with the branch network of the failed bank, or by the share of local banks that are well capitalized. Here we use the predicted values of capital ratios of individual local potential acquirers, $\widehat{\Delta capitalization_{ijt}}$, to construct the same measures.[11] The results are presented in Table 8B, columns 1 and 2, and show that our inferences from Table 8A remain the same. As in Table 8A, we also compute the instrumented capitalization of local potential acquirers whose share of CRE loans is closest to the failed bank. Our instrumented results again mirror those from the simple OLS specification in Table 8A.

One concern with the instrumental variable may be that the house price changes in MSAs without failed bank branches are still correlated with house price changes in MSAs in which the failed bank operates, because of the proximity of the regions. Note that this concern should be mitigated to some extent since we directly account for the state fixed effect μ_s in the regression, which controls for any such correlation between MSAs in the same state. Nevertheless, as a robustness check, we estimate our regressions constructing the IV to exclude MSAs in which the failed bank operates as well as MSAs contiguous to failed bank operations. The results in columns 3 and 4 reveal similar findings. In the last specification (columns 5 and 6) we exclude all MSAs from the states in which the failed bank operates when constructing the IV. We find similar results with this alternative specification as well.

VI.B Robustness to Bid Characteristics and Measures of Resolution Costs

We conclude our analysis by conducting additional robustness tests. We introduce additional controls for the terms of the winning bid to our main results. These include an indicator variable that takes the value of 1 if the deal was for all loans and deposits of the failed bank, an indicator variable that takes the value of 1 if the deal was for no loan but all deposits of the failed bank, an indicator variable that assumes the value of 1 if the deal was for no loans and only the insured deposits of the failed bank, an indicator variable that takes the value of 1 if the transaction includes a loss share agreement, and a variable that indicates the loss share percentage in the first tranche of the loss share agreement. We also include a control for the number of bids in each P&A transaction. We present the results in columns 1 and 2 of Table 8C, and we find our results are robust to the inclusion of bid characteristics.

[11] Even though $capitalization_{jt}$ is at the level of potential acquirer and time, *jt*, the predicted value $\widehat{capitalization}_{ijt}$ is at the level of the potential acquirer, time, and the failed bank, *ijt*, because the instrument is at the failed bank level.

Next, we use an alternative measure of the costs of resolution of a failed bank. Instead of the cost estimates provided by the FDIC, we can measure the actual premia or discounts offered for assets and deposits of the bank by the winning bidder. Bidders can offer to acquire the assets of the failed bank at a discount but also to pay a premium for the deposits of the failed bank (both as a percentage of the failed bank's assets). We take the difference in the discount and the premium to obtain a net discount offered by the bidder on the failed banks' assets and liabilities. We again control for other bid characteristics. The results presented in columns 3 and 4 of Table 8C show that the results with this alternative measure are quantitatively very similar, suggesting that the asset discount and deposit premium are primary inputs into FDIC costs.

VII. Discussion and Interpretation: Fire Sales of Failed Banks

In this section we interpret the facts that we have documented within the framework of fire sales (Shleifer and Vishny, 1992). The insight from Shleifer and Vishny (1992) is that in auctions of distressed assets, potential buyers with the highest valuations may be distressed and are therefore unable to purchase the assets. Auctions of failed banks in our sample are plausibly subject to fire sales. Because of bank run fears, auctions are swift, and bidding generally starts twelve to fifteen days before the scheduled closing of the failed bank. Moreover, because most of these auctions occurred during the great recession and its aftermath, several banks that might have been high-value acquirers were themselves distressed.

For fire sales to affect the allocation of failed banks two conditions have to be met. First, potential acquirers must differ in their ability to use the failed bank. If all potential acquirers can use the failed bank in the same way, then the fire sale cannot affect the allocation. In other words, failed banks have to exhibit asset specificity for fire sales to have meaningful consequences for allocation. Second, the best users of failed banks must be distressed themselves and therefore unable to purchase the failed bank. The failed bank is then purchased by well-capitalized acquirers that are less effective at operating it.

Our first set of results in Section V examines the probability that a given potential acquirer purchases a failed bank. Because failed banks are sold at auctions, potential acquirers whose willingness to pay is higher are more likely to win the auction. Conversely, if certain potential acquirers are more likely to acquire a given failed bank, we conclude that they value the bank more than other potential acquirers. We first show that there are two forces that generate different valuations for a failed bank among potential acquirers. First, geographically closer potential acquirers are more likely to acquire a failed bank, and the effect of distance seems to be related to the deterioration of soft information with distance. These results suggest that potential acquirers' valuations of failed banks, on average, decline with distance. Second, we find that potential acquirers that are in similar lines of business as the failed bank are more likely to purchase a failed bank, suggesting higher valuation by these acquirers. These results establish two dimensions over which acquirers' valuations for a failed bank can differ. Potential acquirers that are geographically close to the failed bank and in similar lines of business are best suited to acquire a failed bank from the perspective of the assets of the failed bank.

Differences in valuations between potential acquirers do not lead to fire sales if the potential acquirers with highest valuations also purchase the failed bank. We show that acquirers with low capitalization, likely distressed themselves, have a lower probability of acquiring a failed bank. Moreover, we examine how the capitalization of the potential acquirers best suited to purchase a failed bank affects auction outcomes: when local banks and banks that are in similar lines of business are poorly capitalized, the failed bank is more likely to be allocated to distant acquirers whose business is less related to that of the failed bank. Our interpretation of these findings is that lower capitalization of potential acquirers that are best suited to purchase a failed bank results in failed banks' allocation to less suitable acquirers. Fire sales introduce distortions into the sale of failed banks.

In Section VI we study how the costs of selling a failed bank incurred by the FDIC are linked to the forces that affect the allocation of failed banks. We show that lower capitalization of the potential acquirers best suited to purchasing a failed bank is related to increased resolution costs for the FDIC. These are the banks that we show are likely to be subject to fire sales and allocated to less suitable acquirers. Overall, our findings suggest that lower capitalization of potential acquirers that are best suited to purchasing a failed bank results in fire sales, which impose a significantly higher cost of failed bank resolutions on the FDIC.

VIII. Conclusion

In this paper we provide simple facts that aid our understanding of failed bank sales. Despite deregulation and progress in information technology, failed bank sales in the great recession and its aftermath remain very local: fewer than 15% of failed banks are sold to banks that do not currently have branches within the same state as the failed bank. In addition, failed banks are more likely to be acquired by banks with similar loan portfolios and in similar lines of business. These two effects interact with the capitalization of potential acquirers. Poor capitalization of nearby acquirers in similar lines of business distorts the allocation of failed banks, which are sold to less similar banks located farther from the failed bank. The results are robust to restricting the data to actual bidders, confirming that they are not driven by auction eligibility criteria imposed by the FDIC. We link facts on banking allocation to the costs to the FDIC of selling a failed bank. When a failed bank's most likely acquirers are poorly capitalized the FDIC incurs significantly higher costs.

These facts can be organized using the fire sales framework of Shleifer and Vishny (1992). Local banks in similar lines of business have the highest valuation for a failed bank. However, if they are distressed as well, then the failed bank has to be sold to a bank whose valuation is lower, but which is well capitalized. The failed bank is then sold at a larger discount, imposing higher costs on the seller, the FDIC.

Selling failed banks is one of the procedures that have been proposed to ensure the functioning of the banking system after negative shocks. This approach is particularly appealing because it keeps the bank in place, potentially preserving the value embodied in the collection of assets and in relationships between bank employees and clients, which may not be easily or quickly replaced. Our facts suggest that the selling process is not frictionless, imposing its own costs. These costs have to be weighed by policy makers and regulators against the costs of other methods of supporting banks.

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Table 1: Summary Statistics

This table presents descriptive statistics of the sample used in the analysis. *Cost* is the cost borne by the FDIC in the resolution process of each failed bank as a percentage of the total assets of the failed bank at assumption. *P50 Tier 1 Capital Ratio of Local Potential Acquirers* is the median Tier1 capital ratio in the set of local potential acquirers of the failed bank. Local potential acquirers are potential acquirers whose branch network overlaps with that of the failed bank in at least one zipcode. *% Well-Capitalized Local Potential Acquirers* is defined as the percentage of local potential acquirers whose Tier 1 capital ratio is above the median Tier 1 capital ratio across local potential acquirers. *COD* is defined as the average Coefficient of Dispersion (COD) in the sales ratio studies of property tax assessments of residential properties in the assessment jurisdictions where the failed bank operates branches. *High COD* is an indicator variable that takes the value one if COD is above median. *Publicly Traded* is an indicator variable that takes the value of one if the failed bank was registered with the SEC in the previous quarter. *Size* is defined as the total assets (RCFD2170) of the bank (in thousands). *Liquidity Ratio* is measured as the ratio between liquid assets (Cash + Fed Funds Sold + Securities (excluding MBS/ABS) and total assets. *% Residential Loans* is measured as the percentage of residential loans relative to total loans (RCFD2122). *% CRE Loans* is measured as the percentage of Commercial and Real Estate (CRE) Loans relative to total loans (RCFD2122). *% C&I Loans* is measured as the percentage of Commercial and Industrial (C&I) loans relative to total loans (RCFD2122). *% Consumer Loans* is measured as the percentage of Consumer loans relative to total loans (RCFD2122). *30-89PD Ratio* is defined as the loans that are 30–89 days past due (RCFD1406) over total loans. *NPL Ratio* is defined as non-performing loans (non-accrual) (RCFD1403) and 90 days or more past due (RCFD1407)) over total loans. *OREO Ratio* is defined as other real estate owned (RCFD2150) divided by total assets. *Unused Commitment Ratio* is defined as unused commitments divided by unused commitments and total loans. *Tier 1 Capital Ratio* is the ratio between Tier 1 (core) Capital and total risk-weighted assets. *Leverage Ratio* is the ratio between Tier 1 (core) Capital and (adjusted) total assets. *Wholesale Funding Ratio* is defined as the sum of large time deposits, subordinated debt and debentures, gross federal funds purchased, repos, and other borrowed money divided by total assets. *% Core Deposits* is total core deposits (transaction accounts + savings deposits + time deposits less than $100,000) divided by total deposits. *Distance* is average pairwise distance (in 100 mile increments) between all pairs of branches of the failed bank and potential acquirer. *State Bank* is defined as an indicator variable that takes the value of one if the bank is regulated by a state regulator. *Multibank BHC* is an indicator variable that takes the value of one if the bank is part of a Bank Holding Company that owns more that one commercial or savings bank. *Distance (% Res. Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in residential loans. *Distance (% CRE Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in CRE loans. *Distance (% CI Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in C&I loans. *Distance (% Cons. Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in consumer loans.

Panel A: Summary Statistics of Failed Banks

	N	Mean	St. Dev.	p25	p50	p75
Resolution Cost and Local Market Characteristics						
Cost	438	0.281	0.120	0.200	0.273	0.366
P50 Tier 1 Capital Ratio of Local Potential Acquirers	424	11.711	1.480	10.575	11.629	12.714
% Well-Capitalized Local Potential Acquirers	424	0.477	0.237	0.333	0.500	0.650
COD	317	13.546	7.477	9.600	11.500	15.640
High COD	317	0.505	0.501	0.000	1.000	1.000
Publicly Traded	434	0.260	0.439	0.000	0.000	1.000
Asset and Financial Characteristics						
Size	438	759,751	2,441,545	102,913	210,851.5	492,491
Liquidity Ratio	438	16.288	7.666	10.621	15.041	20.605
% Residential Loans	438	26.250	19.312	12.311	23.314	32.692
% CRE Loans	438	57.481	19.805	46.353	60.259	70.157
% C&I Loans	438	10.777	8.909	4.544	8.455	14.439
% Consumer Loans	438	2.224	3.160	0.375	1.157	2.844
30-89PD Ratio	438	4.281	3.399	1.975	3.584	5.699
NPL Ratio	438	15.892	9.212	9.523	14.641	19.882
OREO Ratio	438	5.183	4.880	1.686	3.853	7.343
Unused Commitment Ratio	438	5.947	5.622	2.577	4.711	8.347
Tier 1 Capital Ratio	438	1.627	3.203	0.336	1.718	2.900
Leverage Ratio	438	1.231	2.219	0.276	1.260	2.110
Wholesale Funding Ratio	438	32.344	14.117	22.990	31.283	41.214
% Core Deposits Ratio	438	72.056	14.046	63.208	74.108	81.522
State Bank	438	0.649	0.477	0	1	1
Multibank BHC	438	0.055	0.228	0	0	0

Table 1: Summary Statistics (contd.)

Panel B: Summary Statistics of Acquirers

	N	Mean	St. Dev.	p25	p50	p75
Asset Characteristics						
Size	417	11,275,389	38,244,003	504,464	1,405,573	3,628,005
Liquidity Ratio	417	16.754	10.345	9.564	14.907	21.081
% Residential Loans	417	24.531	14.843	14.196	23.459	30.940
% CRE Loans	417	48.698	18.415	36.394	52.013	62.160
% C&I Loans	417	15.034	8.692	8.193	14.058	19.758
% Consumer Loans	417	5.212	7.148	0.969	2.627	7.165
30-89PD Ratio	417	1.323	1.183	0.524	0.968	1.731
NPL Ratio	417	3.924	4.962	1.123	2.301	4.557
OREO Ratio	417	0.964	1.264	0.166	0.522	1.201
Unused Commitment Ratio	417	14.320	8.327	8.866	13.683	18.373
Financial Characteristics						
Tier 1 Capital Ratio	417	16.774	13.211	11.203	13.380	17.093
Leverage Ratio	417	10.695	5.179	8.260	9.690	11.730
Book Equity Ratio	417	11.975	5.236	9.430	11.115	13.224
Wholesale Funding Ratio	417	23.263	9.358	16.790	22.069	28.793
% Core Deposits Ratio	417	80.512	9.145	74.877	81.990	86.855
State Bank	417	0.559	0.497	0	1	1
Multibank BHC	417	0.260	0.438	0	0	1
Proximity to Failed Bank						
Distance	414	2.010	3.524	0.000	1.000	2.000
Distance (% Res. Loans)	416	15.293	14.672	4.691	10.841	21.110
Distance (% CRE Loans)	416	18.944	15.160	7.875	15.370	26.441
Distance (% C&I Loans)	416	8.916	7.723	3.078	7.104	11.992
Distance (% Cons. Loans)	416	4.530	6.630	0.784	1.977	5.999

Table 1: Summary Statistics (contd.)

Panel C: Summary Statistics for all Potential Acquirers

	N	Mean	St. Dev.	p25	p50	p75
Asset Characteristics						
Size	3466810	1,714,011	31,925,725	72,038	150,311	341,356
Liquidity Ratio	3466810	23.825	15.780	12.822	20.147	30.815
% Residential Loans	3409603	31.023	21.430	15.724	26.545	40.800
% CRE Loans	3411532	35.120	21.703	17.078	33.817	50.958
% C&I Loans	3411532	13.226	10.447	6.352	11.305	17.746
% Consumer Loans	3411532	6.671	10.016	1.437	3.914	8.197
30-89PD Ratio	3411532	1.441	1.640	0.348	0.956	1.971
NPL Ratio	3411470	2.629	3.812	0.490	1.486	3.287
OREO Ratio	3457074	0.745	1.473	0.000	0.216	0.843
Unused Commitment Ratio	3404039	10.628	7.726	5.415	9.899	14.820
Financial Characteristics						
Tier 1 Capital Ratio	3464686	21.974	90.736	11.400	13.960	18.610
Leverage Ratio	3464693	11.587	10.588	8.300	9.540	11.660
Book Equity Ratio	3464693	12.069	9.928	8.692	10.123	12.392
Wholesale Funding Ratio	3465970	21.954	11.014	14.362	20.967	28.365
% Core Deposits Ratio	3431750	79.639	11.717	74.227	81.467	87.250
State Bank	3470905	61.1	48.7	0	1	1
Proximity to Failed Bank						
Distance	3428866	9.175	6.069	5.000	8.000	12.000
Distance (% Res. Loans)	3401228	22.085	19.260	7.546	16.560	30.807
Distance (% CRE Loans)	3403145	30.732	20.505	13.528	28.085	45.400
Distance (% C&I Loans)	3403145	10.127	9.582	3.482	7.563	13.786
Distance (% Cons. Loans)	3403145	6.041	9.663	1.207	3.242	7.251

Table 2: Acquisition Likelihood and Failed Bank/Acquirer Characteristics

This table reports the coefficients from a logit regression. The dependent variable Pr(acquisition) takes the value of one if potential acquirer j acquires failed bank i and zero otherwise. *Size (acquirer)* is the standardized value of total assets (RCFD2170) measured using constant 2009:Q1 prices. *% Residential Loans (acquirer)* is measured as the percentage of residential loans relative to total loans (RCFD2122). *% CRE Loans (acquirer)*is measured as the percentage of Commercial and Real Estate (CRE) Loans relative to total loans (RCFD2122). *% C&I Loans (acquirer)* is measured as the percentage of Commercial and Industrial (C&I) loans relative to total loans (RCFD2122). *Tier 1 Capital Ratio (acquirer)* is the ratio of Tier 1 (core) capital and total risk-weighted assets. *Leverage ratio (acquirer)* is the ratio of Tier 1 (core) capital and (adjusted) total assets. *% Core Deposits (acquirer)* is total core deposits (transaction accounts + savings deposits + time deposits less than $100,000) divided by total deposits. Other unreported control variables are: *Liquidity Ratio* is measured as the ratio of liquid assets Cash + Fed Funds Sold + Securities (excluding MBS/ABS) and total assets. *Unused Commitment ratio* is measured as total unused commitments divided by the sum of total unused commitments and total loans. *% Consumer Loans* is measured as the percentage of Consumer loans relative to total loans (RCFD2122). *NPL ratio* is defined as non-performing loans (non-accrual (RCFD1403) and 90 days or more past due (RCFD1407)) over total loans. *OREO ratio* is measured as other real estate owned (RCFD2150) divided by total assets. Standard errors are presented in parentheses, and are clustered at the level of the failed bank's state headquarters.

	(1)	(2)	(3)
		Pr(acquisition)	
Size (acquirer)	0.041***	0.042***	0.041***
	(0.006)	(0.006)	(0.006)
% Residential Loans (acquirer)	0.009*	0.009**	0.009*
	(0.005)	(0.004)	(0.005)
% CRE Loans (acquirer)	0.034***	0.033***	0.036***
	(0.006)	(0.006)	(0.006)
% C&I Loans (acquirer)	0.016***	0.016***	0.017***
	(0.006)	(0.006)	(0.006)
Tier 1 Capital Ratio (acquirer)	0.001***		
	(0.000)		
Leverage Ratio (acquirer)		0.009***	
		(0.004)	
% Core Deposits (acquirer)			0.018***
			(0.005)
Observations	3,385,778	3,385,778	3,384,401
Quarter fixed effects	Yes	Yes	Yes
Failed Bank Controls	Yes	Yes	Yes
Potential-Acquirer Controls	Yes	Yes	Yes

Table 3: Geographic Proximity

Table 3 reports the coefficients from a fixed-effects logit regression. The dependent variable Pr(acquisition) takes the value of one if potential acquirer j acquires failed bank i and zero otherwise. *Distance*is average pairwise distance (in 100 mile increments) between all pairs of branches of the failed bank and potential acquirer. Potential acquirer controls (unreported) include Size, Liquidity Ratio, % CRE Loans, % C&I Loans,, NPL Ratio, OREO Ratio, Unused Commitment Ratio, and Tier1 Capital Ratio. Column (1) of Panel A includes Failed Bank fixed effects and the above potential acquirers controls. The specifications in columns (2) and (3) of Panel A include Potential-Acquirer and Potential-Acquirer/Quarter Fixed-Effects, respectively. The introduction of Potential-Acquirer and Potential-Acquirer/Quarter fixed effects eliminates observations with invariant dependent variables at the level of the Potential-Acquirer and Potential-Acquirer/Quarter, resulting in a reduction of the number of observations from column (1) to columns (2) and (3). Panel B reports the results from a fixed-effects logit regression using the specification in column (3) of Panel A on coastal/non-coastal areas and on high/low house price growth (2001:Q1–2006:Q4) areas. *Coastal* is defined as an indicator variable taking the variable of one if the state headquarter of the failed bank is located in a coastal state, where coastal state is defined as any state with a coastline on the Atlantic, Pacific Ocean, and Great Lakes. *High HPI growth (01-06)* is an indicator variable that takes the value of one if the house price index (HPI) growth in the failed bank's branch service area over the 2001:Q1–2006:Q4 period is greater than the median level of HPI change for all failed banks. The House Price Index growth (01-06) is calculated using the all-transactions indexes at the MSA and state non-metropolitan levels provided by the Federal Housing Finance Agency. We calculate the House Price Index growth for each failed bank by weighting the HPI growth (01-06) variable for each bank by the percentage of deposits of the failed bank in each area. Panel C repeats the analysis of column (3) of Panel A stratifying the sample based on the median levels of CRE, Residential, and C&I loans held by the failed banks in the sample. Standard errors are presented in parentheses, and are clustered at the level of the failed bank's state headquarters.

Panel A: Geographic Distance and Acquisition Likelihood

	(1)	(2)	(3)
		Pr(acquisition)	
Distance	-0.624***	-0.679***	-0.545***
	(0.095)	(0.102)	(0.089)
Observations	3,202,315	93,666	9,231
Failed Bank Fixed-Effects	Yes	Yes	Yes
Potential-Acquirer Controls	Yes	Yes	No
Potential-Acquirer Fixed-Effects	No	Yes	No
Potential-Acquirer/Quarter Fixed-Effects	No	No	Yes

Panel B: Geographic Distance and Acquisition Likelihood: Heterogeneity across Regions

	(1)	(2)	(3)	(4)
		Pr(acquisition)		
	Coastal	Non-Coastal	High HPI growth	Low HPI growth
Distance	-0.420***	-0.712***	-0.375***	-0.865***
	(0.087)	(0.164)	(0.056)	(0.101)
Observations	4,819	4,412	4,644	4,587
Failed Bank Fixed-Effects	Yes	Yes	Yes	Yes
Potential-Acquirer/Quarter Fixed-Effects	Yes	Yes	Yes	Yes

Table 3: Geographic Proximity (cont'd)

Panel C: Geographic Distance and Acquisition: Heterogeneity across Lending Specialization

	(1)	(2)	(3)	(4)	(5)	(6)
	Pr(acquisition)					
	High CRE	Low CRE	High Residential	Low Residential	High C&I	Low C&I
Distance	-0.466***	-0.636***	-0.565***	-0.526***	-0.575***	-0.510***
	(0.090)	(0.117)	(0.118)	(0.098)	(0.123)	(0.081)
Observations	4,607	4,624	4,652	4,579	4,735	4,496
Failed Bank Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Potential-Acquirer/Quarter Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Interaction of Soft Information and Distance

This table reports the results of a fixed-effects logit regression. The dependent variable Pr(acquisition) takes the value of one if potential acquirer j acquires failed bank i and zero otherwise. *Distance* is average pairwise distance (in 100 mile increments) between all pairs of branches of the failed bank and potential acquirer. *COD* is a measure of soft information and is defined as the average Coefficient of Dispersion (COD) in the sales ratio studies of property tax assessments of residential properties in the assessment jurisdictions where the failed bank operates branches. *High COD* is an indicator variable that takes the value one if COD is above the median COD in the sample. *Publicly Traded* is an indicator variable that takes the value of one if the failed bank was registered with the SEC in the previous quarter, and *Large* is an indicator variable that takes the value of one if the total assets of the failed bank are larger than the median size of the subset of failed banks in the quarter prior to failure. All specifications include Failed Bank Fixed-Effects and Potential-Acquirer/Quarter Fixed-Effects. Standard errors are presented in parentheses, and are clustered at the level of the failed bank's state headquarters.

	(1)	(2)	(3)	(4)
	Pr(acquisition)			
Distance	-0.475***	-0.357**	-0.668***	-0.694***
	(0.092)	(0.139)	(0.103)	(0.129)
High COD×Distance	-0.238**			
	(0.095)			
COD×Distance		-0.017*		
		(0.010)		
Publicly Traded×Distance			0.341***	
			(0.101)	
Large×Distance				0.267**
				(0.122)
Observations	6,635	6,635	9,231	9,231
Failed Bank Fixed-Effects	Yes	Yes	Yes	Yes
Potential-Acquirer/quarter Fixed-Effects	Yes	Yes	Yes	Yes

Table 5: Role of Asset Overlap

This table reports the results of a fixed-effects logit regression. The dependent variable Pr(acquisition) takes the value of one if potential acquirer j acquires failed bank i and zero otherwise. Panel A analyzes similarity of loan portfolio composition. Panel B examines the impact of similarity between Lines of Business of Failed Bank and Potential Acquirers. *Distance (% Residential Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in residential loans. *Distance (% CRE Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in CRE loans. *Distance (% CI Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in C&I loans. *Distance (% Consumer Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in consumer loans. *Fiduciary Business in Both* is an indicator variable that takes the value of one if both the failed bank and potential acquirer report strictly positive revenues from fiducuary business in the quarter prior to the resolution. *Insurance Business in Both* is an indicator variable that takes the value of one if both the failed bank and potential acquirer report strictly positive revenues from insurance activities in the quarter prior to the resolution. *Brokerage Business in Both* is an indicator variable that takes the value of one if both the failed bank and potential acquirer report strictly positive revenues from brokerage activities in the quarter prior to the resolution.*Lease Financing Business in Both* is an indicator variable that takes the value of one if both the failed bank and potential acquirer report strictly positive revenues from lease Financing activities in the quarter prior to the resolution. The same line of business segment variables (*Fiduciary Business in Both, Insurance Business in Both*, *Brokerage Business in Both*, *Lease Financing Business in Both*) are only defined for commercial banks because the regulatory financial reports of savings banks prior to the discontinuation of the Office of Thrift Supervision did not breakdown revenue by business segment. All specifications include Failed Bank Fixed-Effects and Potential-Acquirer/Quarter Fixed-Effects. Standard errors are presented in parentheses, and are clustered at the level of the failed bank's state headquarters.

Panel A: Distance of Loan Portfolio Composition

	(1)	(2)	(3)	(4)	(5)
			Pr(acquisition)		
Distance (% Residential Loans)	-0.012**				-0.005
	(0.005)				(0.006)
Distance (% CRE Loans)		-0.012***			-0.011**
		(0.005)			(0.005)
Distance (% C&I Loans)			-0.007		-0.005
			(0.008)		(0.008)
Distance (% Consumer Loans)				-0.002	0.004
				(0.008)	(0.007)
Distance	-0.543***	-0.540***	-0.543***	-0.544***	-0.540***
	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)
Observations	9,225	9,225	9,225	9,225	9,225
Failed Bank Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Potential-Acquirer/quarter Fixed-Effects	Yes	Yes	Yes	Yes	Yes

Table 5: Role of Asset Overlap (contd.)

Panel B: Lines of Business Overlap

	(1)	(2)	(3)	(4)	(5)
			Pr(acquisition)		
Fiduciary Business in Both	0.863***				0.989***
	(0.306)				(0.342)
Insurance Business in Both		0.772***			0.748***
		(0.205)			(0.192
Brokerage Business in Both			0.414*		0.246
			(0.216)		(0.228)
Lease Financing Business in Both				0.065	-0.043
				(0.623)	(0.640)
Distance	-0.572***	-0.582***	-0.579***	-0.579***	-0.580***
	(0.097)	(0.099)	(0.098)	(0.098)	(0.097)
Observations	7,506	7,416	7,416	7,416	7,416
Failed Bank Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Potential-Acquirer/quarter Fixed-Effects	Yes	Yes	Yes	Yes	Yes

Table 6: Financial Health of Local Banks

Table 6 reports the results of a fixed-effects logit regression. The dependent variable Pr(acquisition) takes the value of one if potential acquirer j acquires failed bank i and zero otherwise. *Tier 1 Capital Ratio (potential acquirer)* is the Tier 1 capital ratio of the potential acquirer. *Leverage Ratio (potential acquirer)* is the common leverage ratio of the potential acquirer (the ratio of Tier 1 (core) capital and (adjusted) total assets). *Distance* is average pairwise distance (in 100 mile increments) between all pairs of branches of the failed bank and potential acquirer. *Distance (% CRE Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in CRE loans. *P50 Tier 1 Capital Ratio of Local Potential Acquirers* is defined as the median Tier 1 capital ratio of the failed bank's local potential acquirers. Local potential acquirers are potential acquirers whose branch network overlaps in at least one zip code with the branch network of the failed bank. *% Well-Capitalized Local Potential Acquirers* is defined as the percentage of local potential acquirers whose Tier 1 capital ratio is above the median Tier 1 capital ratio across local potential acquirers. *P50 Tier 1 Capital Ratio Close CRE Potential Acquirers* is defined as the median Tier 1 capital ratio in the group of close CRE potential acquirers. Close CRE potential acquirers are potential acquirers that are within the first quartile of loan portfolio closeness according to the CRE distance metric. *% Well-Capitalized Close CRE Potential Acquirers* is defined as the percentage of close CRE potential acquirers whose Tier 1 capital ratiosis above the median Tier 1 capital ratio across local potential acquirers. Potential-Acquirer controls include Size, Liquidity Ratio, % Residential Loans, % CRE Loans, % C&I Loans, % Consumer Loans, 30-89PD Ratio, NPL Ratio, OREO Ratio, Unused Commitment Ratio. Specifications (3)-(6) include Failed Bank Fixed-Effects and Potential-Acquirer/Quarter Fixed-Effects. Standard errors are presented in parentheses, and are clustered at the level of the failed bank's state headquarters.

	(1)	(2)	(3)	(4)	(5)	(6)
			Pr(acquisition)			
Tier 1 Capital Ratio (potential acquirer)	0.043***					
	(0.014)					
Leverage Ratio (potential acquirer)		0.010***				
		(0.003)				
P50 Tier 1 Capital Ratio of Local Potential Acquirers×Distance			-0.098***			
			(0.025)			
% Well-Capitalized Local Potential Acquirers×Distance				-0.380***		
				(0.117)		
P50 Tier 1 Capital Ratio Close CRE Potential Acquirers×CRE Distance					-0.005**	
					(0.002)	
% Well-Capitalized Close CRE Potential Acquirers×CRE Distance						-0.004*
						(0.002)
Distance	-0.624***	-0.626***	-0.550***	-0.367***		
	(0.095)	(0.087)	(0.084)	(0.108)		
CRE Distance					-0.018***	-0.007
					(0.005)	(0.017)
Observations	3,202,315	3,202,315	8,924	8,924	9,343	9,343
Failed Bank Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Potential-Acquirer Controls	Yes	Yes	No	No	No	No
Potential-Acquirer/quarter Fixed-Effects	No	No	Yes	Yes	Yes	Yes

Table 7: Robustness: Eligibility Requirements

Table 7 reports the results of a fixed-effects logit regression. The dependent variable Pr(acquisition) takes the value of one if potential acquirer j acquires failed bank i and zero otherwise. Columns (1)–(5) analyze the likelihood of acquisition in the subset of potential acquirers that are eligible to bid for a failed bank according to the FDIC's size eligibility criteria. Columns (6)–(10) repeat the analysis in the subset of potential acquirers j that placed a bid in the auction of failed bank i. *Distance*is average pairwise distance (in 100 mile increments) between all pairs of branches of the failed bank and potential acquirer. *Distance (% CRE Loans)* is the absolute difference between the failed bank's and the potential acquirer's percentage of total loans held in CRE loans. *Tier 1 Capital Ratio (potential acquirer)* is the Tier 1 capital ratio of the potential acquirer. *P50 Tier 1 Capital Ratio of Local Potential Acquirers* is defined as the median Tier 1 capital ratio of the failed bank's local potential acquirers. Local potential acquirers are potential acquirers whose branch network overlaps in at least one zip code with the branch network of the failed bank. *% Well-Capitalized Local Potential Acquirers* is defined as the percentage of local potential acquirers whose Tier 1 capital ratio is above the median Tier 1 capital ratio across local potential acquirers. Specifications (1)–(5) include Failed Bank Fixed-Effects and Potential-Acquirer/Quarter Fixed-Effects. Specifications (6)–(10) include Failed Bank Fixed-Effects and Potential Acquirer controls. Potential-Acquirer controls include Size, Liquidity Ratio, % CRE Loans, % C&I Loans, % Consumer Loans, NPL Ratio, OREO Ratio, Unused Commitment Ratio. Standard errors are presented in parentheses, and are clustered at the level of the failed bank's state headquarters.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Pr(acquisition)					
Distance	-0.526***	-0.519***	-0.572***	-0.518***	-0.344***	-0.081**	-0.076**	-0.080**	-0.097***	-0.088***
	(0.096)	(0.087)	(0.095)	(0.089)	(0.126)	(0.032)	(0.031)	(0.031)	(0.031)	(0.026)
CRE Distance		-0.010					-0.015*			
		(0.008)					(0.009)			
Tier 1 Capital Ratio (potential acquirer)			0.037**					0.026*		
			(0.015)					(0.014)		
P50 Tier 1 Capital Ratio of Local Potential Acquirer×Distance				-0.083***					-0.070***	
				(0.023)					(0.019)	
% Well-Capitalized Local Potential Acquirer×Distance					-0.359**					-0.375***
					(0.145)					(0.134)
Observations	5,248	5,242	763,692	4,987	4,987	943	940	943	916	916
Eligibility Criteria	FDIC	FDIC	FDIC	FDIC	FDIC	Bidder	Bidder	Bidder	Bidder	Bidder
Target-Specific fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Potential-Acquirer Controls	No	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Potential-Acquirer/quarter Fixed-Effects	Yes	Yes	No	Yes	Yes	No	No	No	No	No

Table 8: Costs of Resolution

Panel A of Table 8 reports the results of OLS regressions. The dependent variable *Cost* is the cost borne by the FDIC in the resolution process of each failed bank as a percentage of the total assets of the failed bank at assumption. *P50 Tier 1 Capital Ratio of Local Potential Acquirers* is the median Tier1 capital ratio in the set of local potential acquirers of the failed bank. Local potential acquirers are potential acquirers whose branch network overlaps in at least one zip code with the branch network of the failed bank. *% Well-Capitalized Local Potential Acquirers* is defined as the percentage of local potential acquirers whose Tier 1 capital ratio is above the median Tier 1 capital ratio across local potential acquirers. *P50 Tier 1 Capital Ratio of Local Potential Acquirers & CRE Overlap* is defined as the median Tier1 capital ratio in the set of local potential acquirers that are also within the first quartile of loan portfolio closeness according to the CRE distance metric. Loan portfolio quartiles are constructed based on the entire sample. *% Well-Capitalized Local Potential Acquirers & CRE Overlap* is defined as the percentage of local potential acquirers whose Tier 1 capital ratio is above the median Tier 1 capital ratio across local potential acquirers and are also within the first quartile of loan portfolio closeness according to the CRE distance metric.*Publicly Traded* is an indicator variable that takes the value of one if the failed bank was registered with the SEC in the previous quarter. *High COD* is an indicator variable that takes the value one if COD is above the median COD.*P50 CRE Distance of Local Potential Acquirers* is the median of the absolute difference between the share of CRE loans in the loan portfolio of the failed bank and the share of CRE loans in the group of local potential acquirers. Other failed bank controls include Size, Liquidity Ratio, % CRE Loans, % C&I Loans, NPL Ratio, OREO Ratio, Unused Commitment Ratio, and Tier1 Capital Ratio. Panel B of Table 8 repeats the analyses in specifications (1) and (2) of Panel A using instrumented values of Tier1 capital ratio to construct the local capitalization variables. The columns of panel B present the results for different sub-samples used in the computation of the instrumental variable (described in the table). Panel C of Table 8 introduces additional controls for the terms of the winning bid. The dependent variable in columns 1 and 2 is *Cost*, and in columns 3 and 4 is *Asset Discount* which is defined as the discount on assets bought by the acquirer minus the premium offered by the acquirer for the deposits of the failed bank (both as a % of the assets of the failed bank at the time of closure). Bid characteristics include *All Bank & All Deposits* which is an indicator variable that takes the value of one if the deal was for all loans and deposits of the failed bank, *No Loans & All Deposits* which is an indicator variable that takes the value of one if the deal was for no loans and all deposits of the failed bank, *No Loans & Insured Deposits* which is defined as an indicator variable that takes the value of one if the deal was for no loans and only the insured deposits of the failed bank, *Loss Share Agreement* which is an indicator variable that takes the value of one if the transaction includes a loss share agreement between the FDIC and the winning bidder, and *Loss Share % (First Tranche)* that represents the loss share percentage assumed by the regulator in the first tranche of the loss share agreement. We also include *Number of Bids* which captures the number of bids in each P&A transaction. Standard errors are presented in parentheses, and are clustered at the level of the failed bank's state headquarters.

Panel A: OLS Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Cost				
P50 Tier 1 Capital Ratio of Local Potential Acquirers	-0.017***							-0.016***	
	(0.005)							(0.004)	
% Well-Capitalized Local Potential Acquirers		-0.083**							-0.071***
		(0.032)							(0.034)
P50 Tier 1 Capital Ratio of Local Potential Acquirers & CRE Overlap			-0.004*						
			(0.002)						
% Well-Capitalized Local Potential Acquirers & CRE Overlap				-0.033**					
				(0.015)					
Publicly Traded					-0.037**			-0.034**	-0.033**
					(0.015)			(0.015)	(0.015)
High COD						0.022*			
						(0.012)			
P50 CRE Distance of Local Potential Acquirers							0.001*	0.001*	0.001*
							(0.001)	(0.001)	(0.001)
Observations	423	424	359	359	433	316	423	418	418
Adjusted R^2	0.575	0.539	0.572	0.571	0.515	0.540	0.529	0.550	0.556
Failed Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Failed Bank state Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Costs of Resolution (contd.)

Panel B: Regressions using Instrumented Local Capitalization Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Cost					
P50 Tier 1 Capital Ratio of Local Bidders	-0.008***		-0.007**		-0.007***	
	(0.003)		(0.003)		(0.002)	
% Well-Capitalized Local Bidders		-0.052**		-0.060**		-0.062**
		(0.022)		(0.024)		(0.028)
Observations	420	420	420	420	415	415
Adjusted R^2	0.540	0.533	0.537	0.535	0.544	0.541
Excluded Sample	Failed Bank MSA		Failed Bank MSA & Adjoining MSAs		Failed Bank State	
Target Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Failed Bank state fixed-effects?	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: OLS Regressions controlling for Bid Characteristics

	(1)	(2)	(3)	(4)
	Cost		Asset Discount	
P50 Tier 1 Capital Ratio of Local Bidders	-0.007*		-0.009***	
	(0.004)		(0.003)	
% Well-Capitalized Local Bidders		-0.070***		-0.067**
		(0.020)		(0.026)
Observations	422	422	420	420
Adjusted R^2	0.296	0.305	0.589	0.590
Target Controls	Yes	Yes	Yes	Yes
Bid Characteristics	Yes	Yes	Yes	Yes
Quarter fixed effects?	Yes	Yes	Yes	Yes
Failed Bank state fixed-effects?	Yes	Yes	Yes	Yes

Figure 1: Number of Bank Failures over Time

Figure 1 plots the time series of bank failures (irrespective of resolution method) during the period 1994–2013. Data is provided by the Federal Deposit Insurance Corporation. The time series includes the failed banks whose resolution process was a P&A transaction or a deposit payoffs but does not include open bank assistances. The time series document the spike in bank failures that occured since 2008 after a relatively calm period from 1994 until 2007.

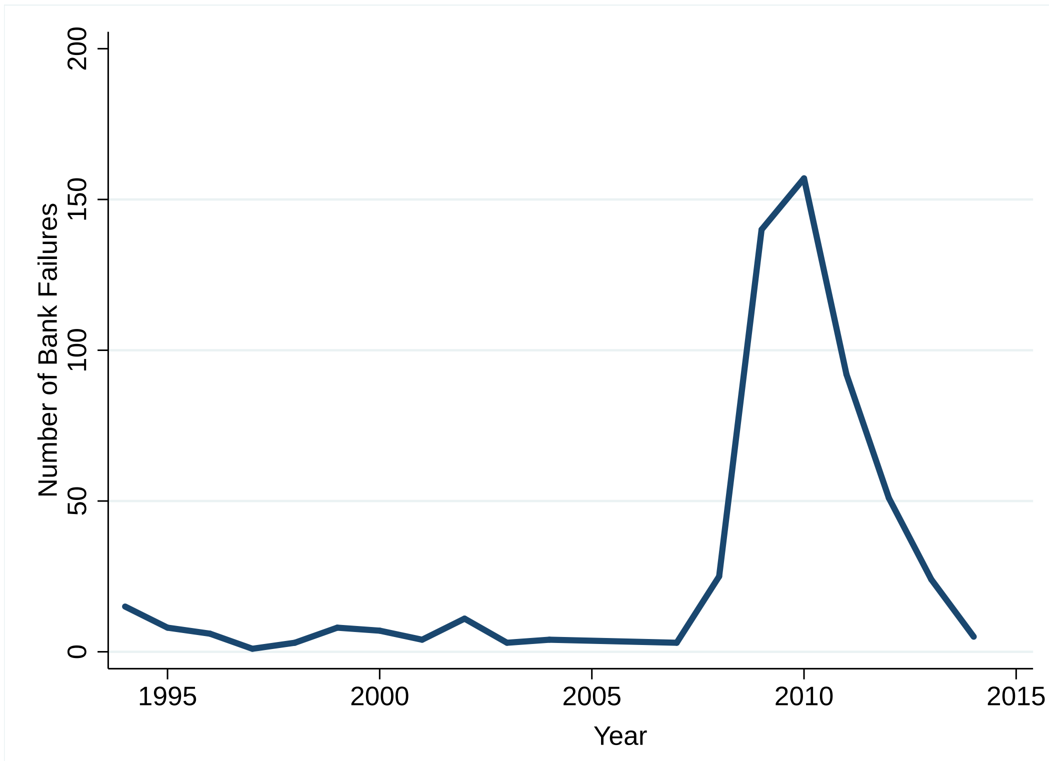


Figure 2: Kernel Density of FDIC Resolution Costs

Figure 2a represents the epanechnikov kernel density of the total resolution costs (red dashed line) incurred by the FDIC in the resolution processes of failed banks since 2007. The solid blue line represents the kernel density of the total assets (in millions of dollars) of the failed banks in the quarter immediately preceding their failure. Figure 2b represents the kernel density of cost of resolution as a percentage of total assets of the failed banks at the time of resolution. The sample covers bank failures from 2007 until the end of 2013.

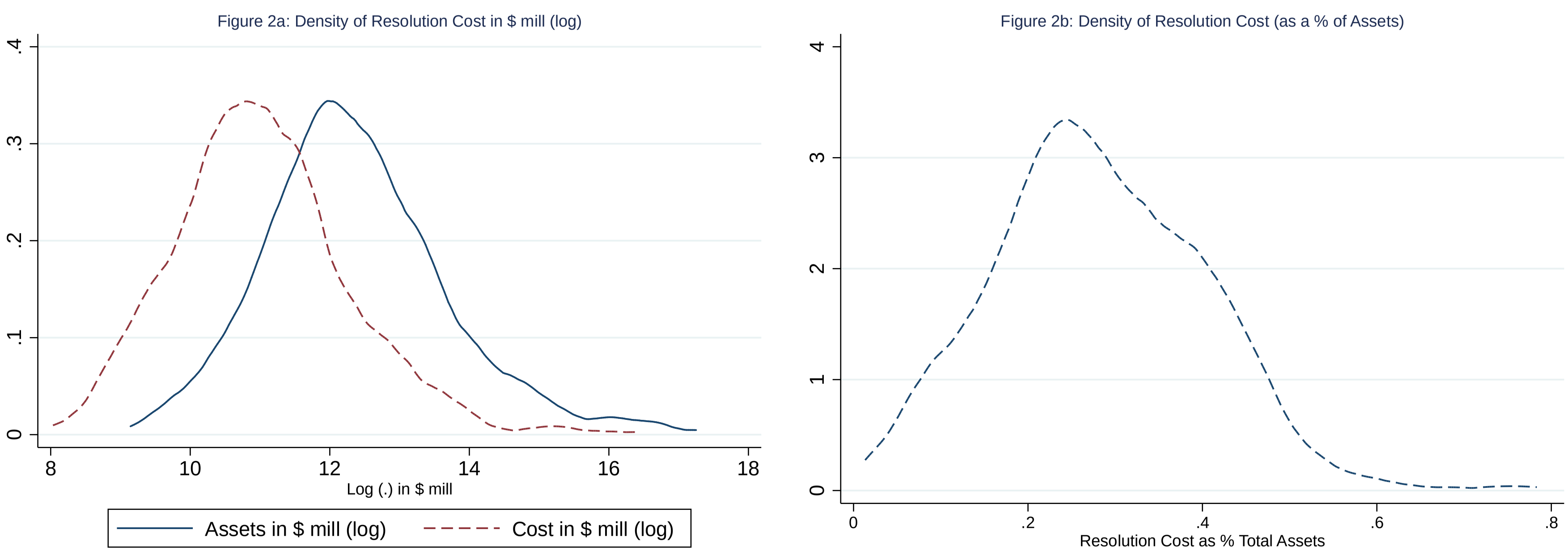
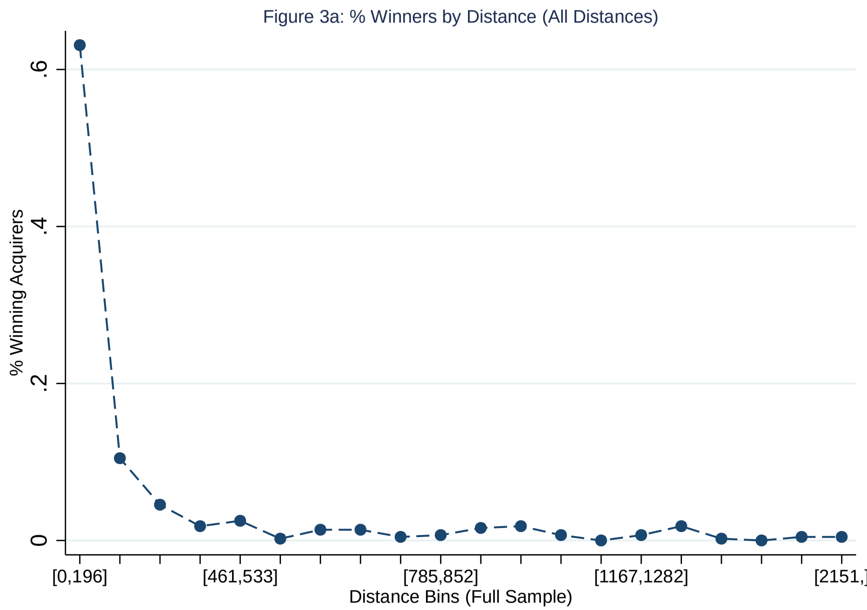


Figure 3: Bank Sales and Distance

Figure 3 plots the share of failed banks (as a % of total failed banks during the sample period) that were assumed by potential acquirers in each of 20 distance bins. Figure 3a plots the share of acquisitions by distance percentile bin. Each percentile bin is defined by assigning 5% of all potential acquirers to 20 distance bins based on the average distance between their branch network and the branch network of each failed bank. The first bin in Figure 3a shows that approximately 65% of the failed banks are sold to potential acquirers whose branch networks are on average less than 196 miles from the branch network of the failed bank. Figure 3b represents the share of acquisitions by distance bin in the subset of potential acquirers within a 200 mile average branch network distance from the failed bank. Each distance bin is defined by assigning 5% of all potential acquirers within 200 miles of the failed bank to 20 distance bins based on the average distance of their branch network to that of the failed bank. The first bin in Figure 3b indicates that approximately 12.5% of the failed banks are sold to potential acquirers whose branch networks are on average less than 21 miles from the branch network of the failed bank



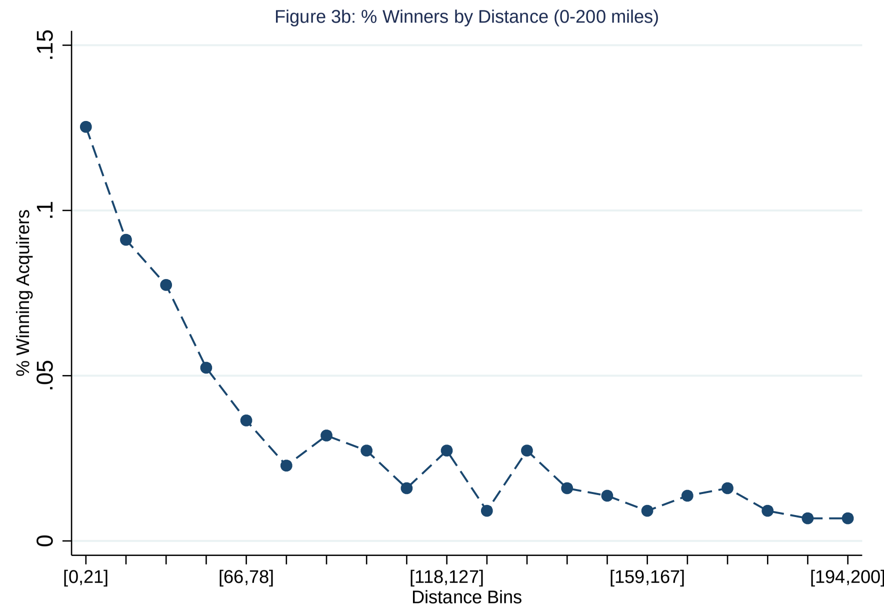
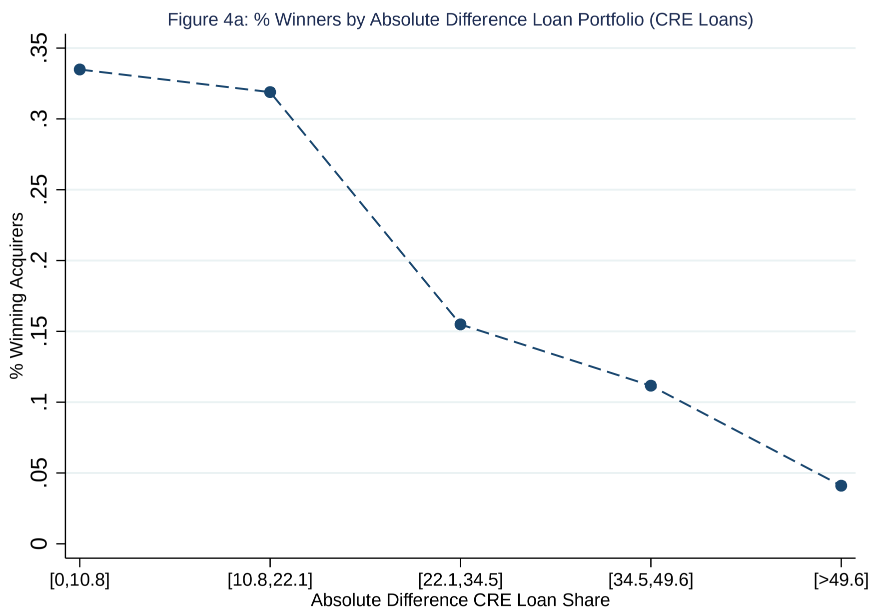


Figure 4: Bank Sales and Asset Specificity - Lending Composition

Figure 4 plots the share of failed banks (as a % of total failed banks during the sample period) that were assumed by potential acquirers in each portfolio distance quintile. Figure 4a plots the percentage of failed banks sold to potential acquirers in each quintile of absolute difference in the share of CRE loans between the failed bank and the potential acquirers. The first quintile bin in Figure 4a indicates that 33% of the failed banks are sold to potential acquirers whose CRE loan share is within 10.8 percentage points of the CRE loan share of the failed bank. Figure 4b plots the percentage of failed banks sold to potential acquirers in each quintile of absolute difference in the share of residential loans between the failed bank and the potential acquirers. The first quintile bin in Figure 4b indicates that approximately 29% of the failed banks are sold to potential acquirers whose Residential loan share is within 6% of the residential loan share of the failed bank.



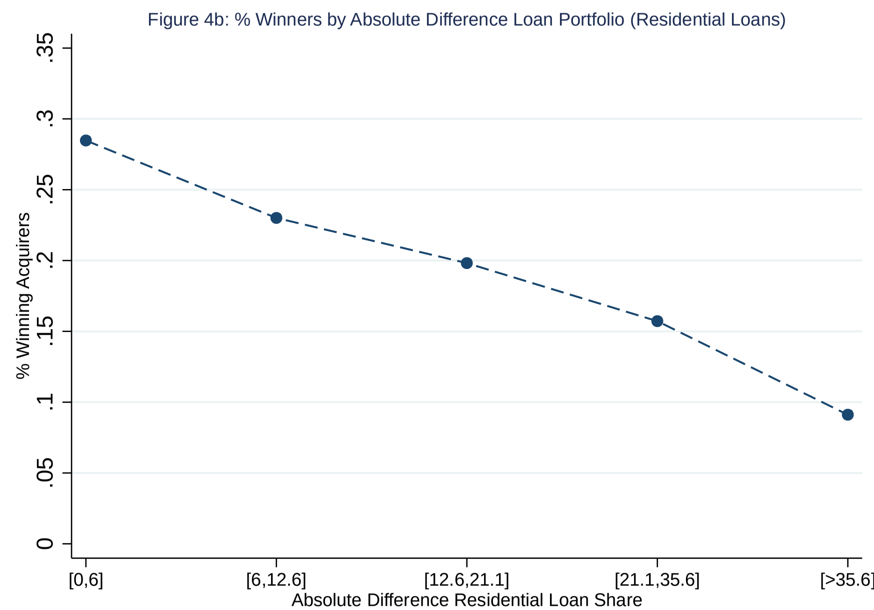
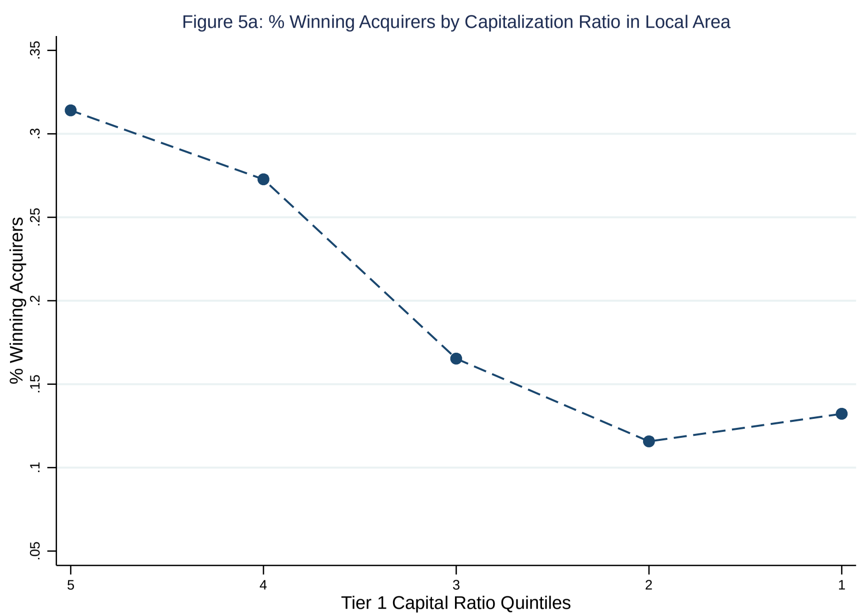


Figure 5: Ability to Pay - Capitalization of Local Potential Acquirers and Similar Portfolio Potential Acquirers and Asset Allocation

Figures 5a and 5b represent the share of failed banks acquired by local potential acquirers and by potential acquirers with similar loan portfolios in each Tier 1 Capital ratio quintile. In Figure 5a potential acquirer is defined as a local potential acquirer if its branch network overlaps with that of the failed bank in at least one zip code area. In Figure 5b potential acquirers with similar loan composition are defined as those potential acquirers whose absolute difference in the share of CRE loans is within the first quartile of that measure, with quartiles constructed based on entire sample.



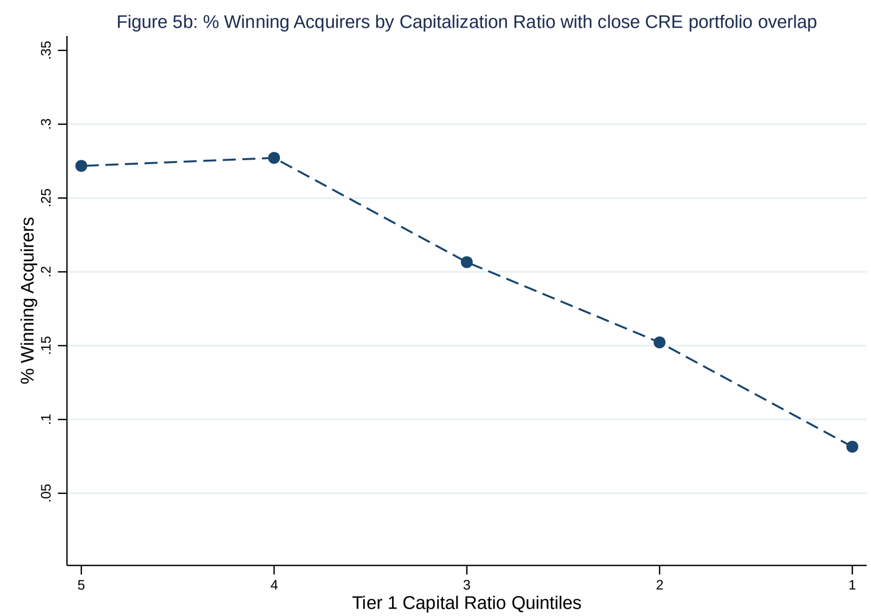


Figure 6: Resolution Costs and Capitalizaiton of Local Potential Acquirers

Figure 6 represents the average resolution cost (as a percentage of the failed banks' assets) for each quintile bin based on capitalization of local potential acquirers. A potential acquirer is defined as a local potential acquirer if its branch network overlaps with that of the failed bank in at least one zip code area. Quintile bins in figure 6a are based on the percentage of local potential acquirers holding an above median level of Tier 1 capital ratio . In figure 6b quintile bins are based on the median Tier 1 capital ratio of local potential acquirers. Both figures suggest that failed banks whose local potential acquirers are not well capitalized are more costly to resolve.

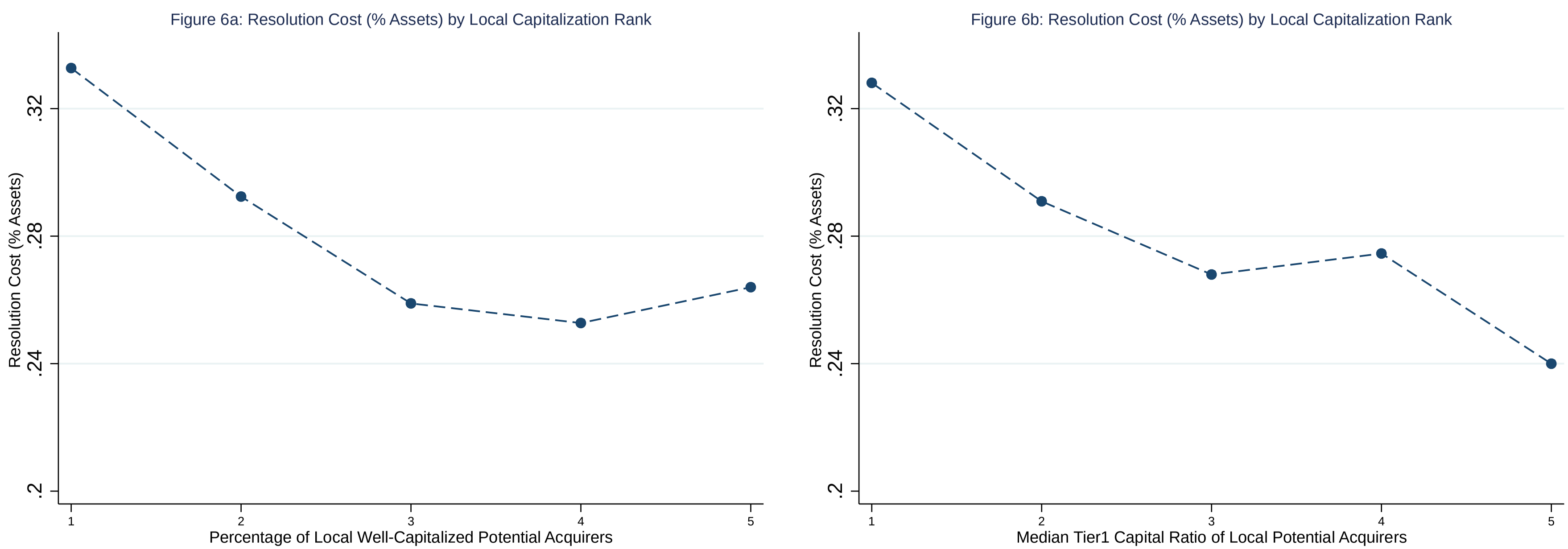


Figure A.1: Bank Sales and Minimum Distance

Figure A.1 plots the share of failed banks (as a % of total failed banks during the sample period) that were assumed by potential acquirers in each of 20 distance bins. Figure A.1a plots the share of acquisitions by distance percentile bin, in which each percentile bin is defined by assigning all potential acquirers to 20 distance bins based on the minimum distance between their branch network and the branch network of each failed bank. The first bin in Figure A.1a shows that approximately 80% of the failed banks are sold to potential acquirers that have at least one branch within 147 miles from a branch in the branch network of the failed bank. Figure A.1b represents the share of acquisitions by distance bin in the subset of potential acquirers within a 200 mile minimum branch network distance from the failed bank. Each distance bin is defined by assigning each potential acquirer within 200 miles minimum distance of the failed bank to 20 distance bins. The first bin in Figure A.1b indicates that approximately 33% of the failed banks are sold to potential acquirers with at least one branch within 3 miles from a branch in the branch network of the failed bank