Three Decades of Failed Bank Acquisitions

Laima Spokeviciute, Hossein, Jahanshahloo, Kevin Keasey, Francesco Vallascas[1,2]

Abstract

Using more than 30 years of data, we document that the acquisition of failed US commercial banks through FDIC-managed Purchase and Assumption (P&A) transactions leads to long-term improvements in the profitability and loan risk of the combined entity and has no detrimental effects on its capital adequacy. These results are generally stronger for transactions with greater potential for economies of scale and efficiency gains. Furthermore, geographic similarity in the branch network of the acquirer and the target marginally improves the profitability of the combined entity, while a greater business similarity between the merged banks has no effect on deal outcomes. Additional tests show that the presence of regulatory subsidies also improves the profitability of the combined entity. Finally, we find no support for theoretical predictions about the misallocation of failed bank assets in the presence of widespread failures in local markets. Our findings are important for the understanding of the consequences of bank resolution through assisted M&As.

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1 Introduction

Since the 1930s the Federal Deposit Insurance Corporation (FDIC) has managed thousands of resolutions of failed US commercial banks via Purchase and Assumption (P&A) transactions. A P&A transaction resembles a first-price sealed bid auction through which the FDIC sells some or

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[2] Please address all correspondence to Laima Spokeviciute, Cardiff Business School, The University of Cardiff, Aberconway Building, Colum Road, Cathays, Cardiff, CF10 3EU, UK; SpokeviciuteL@cardiff.ac.uk. Hossein Jahanshahloo is at Cardiff Business School, The University of Cardiff, UK; JahanshahlooH@cardiff.ac.uk. Kevin Keasey is at Leeds University Business School, The University of Leeds, UK; kk@lubs.leeds.ac.uk. Francesco Vallascas is at Durham University Business School, Durham University, UK; francesco.vallascas@durham.ac.uk.

all assets and liabilities of the failed bank to a healthier institution. These acquisitions can generate significant costs for the FDIC, but they might also produce benefits via the redeployment of failed assets and by preserving relationships with the clients of the failed banks (Granja et al., 2017).

Assessing the full spectrum of such benefits is then pivotal for the FDIC to understand whether the resolution process via these deals allows an effective reallocation of resources within the banking system. In this respect, long-term analyses that examine *actual* bank performance changes associated with the P&A deals can offer valuable information on the effects of the resolution for the banks involved in the transaction and on the potential drivers of these effects. Thus, long-term studies can complement the wider literature on short-term wealth effects of P&A deals for the bidder shareholders (see Bertin et al., 1989; Cochran et al., 1995; Cowan and Salotti, 2015; James and Wier, 1987; Pettway and Trifts, 1985; Zhang, 1997). Such short-term investigations provide indications on the (market-based) *expected* long-term performance of the deals, but they fail to account for any possible deviation of the expected effects from the actual long-term effects (DeLong and DeYoung, 2007; Fraser and Zhang, 2009).

Despite their potential to be highly informative for regulators, long-term studies on P&A deals have to date played only a very marginal role in the literature (see, Cowan et al., 2022; Peristiani, 1997; Vij, 2020). Furthermore, the existing long-term studies provide evidence that is limited to some specific periods and generally related to a small set of bank outcomes. This paper offers novel indications on the long-term effects of P&A deals by implementing an empirical framework based on the long-term profitability, capital and loan risk effects of these deals and a dataset that spans over three decades starting from 1984.[3] Furthermore, we exploit the length of the sample

[3] A long-term analysis might also be based on stock performance of the acquiring firms. However, this sort of analysis would place emphasis on listed institutions that represent only a small sub-set of the banks in our sample. Additionally, stock prices over a long period might be more affected than accounting data by numerous confounding factors related to the fact that failed bank acquisitions via the FDIC typically occur in the extremely volatile periods of banking crises.

period not only to show the long term dynamics of the outcomes of the deals, but also to identify to what extent deal characteristics that are typically investigated in the context of unassisted M&As, and features specific to P&A transactions, are behind the long-term outcomes we observe.

Our empirical strategy to investigate the long-term effects of P&A transactions is based on three elements. First, we combine the accounting information of the acquirer and the target prior to the deal (Cornett and Tehranian, 1992; Cornett et al., 2006; Igan et al., 2022; Papadimitri et al., 2019; Peristiani, 1997). Second, we contrast the performance of these combined entities with the performance of a matched-control group of non-acquiring banks. Third, we conduct our tests over a period ranging from up to 20 quarters before and 20 quarters after the event in a panel setting, which controls for time invariant bank characteristics and time variant macro factors via bank and state × quarter fixed effects. These methodological choices allow us to focus on the effects of the deals in terms of the redeployment of failed bank assets, rather than on the consequences for bank shareholders, and exclude the possibility of capturing wide market trends with our investigation.

We start by showing that P&A transactions are associated with an increase in profitability and a reduced loan risk for the combined entity relative to the matched sample and are not detrimental for the capital strength of the combined entity. We show that the impact on profitability and loan risk is also economically large. We further document that our results are consistent when we draw focus on the P&A transactions that occurred during the most recent wave of P&A deals identified as in Cowan and Salotti (2015). The baseline results hold under alternative specifications, including when we estimate a dynamic model that accounts for a potentially different quarterly evolution of bank profitability, capital and loan risk in the 5 years after the completion of the deal, and when we change matching strategies to rule out the possibility of mechanical findings due to the combined entity approach. Ultimately, our initial analyses suggest that P&A deals are beneficial over the long-term in redeploying failed bank assets.

Next, we examine which factors that have been identified as potential drivers of performance benefits in unassisted M&As matter in the context of P&A deals. Such investigation is important. Indeed, documenting which of these factors influence the long-term success of the resolution relates to the debate on which potential acquirers should be favored by the FDIC in the bidding process to obtain most benefits from the deals (Granja et al., 2017; Igan et al., 2022).

We begin by following the conventional argument in the M&A literature according to which performance benefits may arise from the possibility for the combined entity to reach scale economies (DeLong, 2003; DeYoung et al., 2009; Humphrey and Vale, 2004; Peristiani, 1997). Along these lines, we document that the most successful P&A deals are those with larger potential to generate economies of scale. We then build on the evidence in Berger and Humphrey (1992) and Hannan and Pilloff (2009) showing that the acquirer can have the ability to improve the efficiency of the target, and document stronger results also in P&A deals with higher potential to generate efficiency gains. Instead, we show that deals characterized by a stronger business similarity between the target and the acquirer do not lead to better outcomes than other deals, while more geographic similarity, as measured by branch-network overlap between the target and the acquirer, seems to be marginally beneficial only for profitability. Therefore, this latter result is not consistent with the evidence reported by Levine et al. (2020) for unassisted bank M&As, wherein geographic diversification seems to be beneficial for the outcomes generated by the deals. Ultimately, our analyses suggest that most of the heterogeneity in the outcome of P&A deals is related to economies of scale and efficiency gains.

We progress by testing whether features that are specific to P&A transactions also influence their long-term success. Initially, we show that, at least in terms of profitability, our findings reflect the importance of a regulatory subsidy in favor of the acquirer. We find larger profitability improvements in deals characterized by larger resolution costs for the FDIC. This is consistent with the view that resolution costs represent a proxy of the market value of the equity of the failed banks that the FDIC transfers to the acquirer, as documented by Bennett and Unal (2015).

Next, we focus on the impact of the shared-loss agreement (SLA) introduced by the Federal Deposit Insurance Corporation Improvement Act (FDICIA) in December 1991. The presence of this agreement implies that the losses generated by a pool of the assets of the failed bank might be charged against the insurance fund after they are sold to the acquirers. We isolate the impact of SLAs on our findings by comparing the results of deals with such agreements with those of a matched sample of deals without SLAs to account for the selection of the agreement being potentially endogenous with respect to certain deal characteristics. We find that SLAs primarily result in a more pronounced increase only in terms of profitability for the combined entity. These findings are, at least in part, again consistent with the evidence on the benefits of regulatory subsidy for the outcome of the deal.

In the final part of our study, we build on the theoretical framework proposed by Acharya and Yorulmazer (2008), where the presence of numerous bank failures decreases the pool of potential acquirers and increases the likelihood that failed bank assets are allocated to inefficient users. A sub-optimal liquidation process would then be observed especially in periods where bank failures are numerous and P&A transactions should be particularly necessary to reduce systemic externalities. However, by investigating the heterogeneity of our results by the relative number of bank failures in local banking markets, we do not find support for this argument. We observe similar consequences for transactions when bank failures are numerous and when the number of bank failures is small. Furthermore, we show that this conclusion is not driven by a particular sub-sample of deals and document that the deals in high failure intensity periods lower the default risk of the combined entity relative to the control group. Hence, our findings suggest that the stability benefits from redeploying failed bank assets are present when P&As are more necessary from a systemic perspective.

Our paper relates to prior work on the short-term performance effects of P&A transactions. Most of these analyses focus on the eighties and nineties (Bertin et al., 1989; Cochran et al., 1995; Gupta et al., 1997; James and Wier, 1987; Pettway and Trifts, 1985; Zhang, 1997). Except for Gupta et al. (1997), who find no significant abnormal returns for failed thrift acquirers in the post-FIRREA period, the conclusion from these early investigations is that failed bank acquisitions generate excess returns to the acquiring institutions. Cowan and Salotti (2015) confirm positive short-term effects also in the period from 2008-2013 and interpret their findings as indicative of wealth transfer from the FDIC to the shareholders of the acquiring banks. Although informative, the short-term pricing of the events might also reflect an inadequate understanding of the deal by market participants because of information problems, rather than a proper indication of the expected long-term benefits of the deal (DeLong and DeYoung, 2007; Fraser and Zhang, 2009). Furthermore, some of the specificities of P&A deals, such as the short time necessary to complete the deal and the related limited due diligence (Granja, 2013), may make this argument particularly pertinent for such deals. Thus, our analyses may be seen as complementing the evidence on the announcement effects of P&A transactions by documenting whether the expected benefits anticipated by event studies indeed materialize over the long-term.

The potential inconsistencies between short-term and long-term evidence are also highlighted by the handful of studies that attempt to provide direct indications on the long-term effects of the acquisition of failed banks. These long-term studies show a far less consistent picture than the short-term analyses. The contrasting conclusions are plausibly due also to methodological differences in terms of sample period, the choice of the bank outcome under investigation and the econometric setting. For instance, Peristiani (1997) finds a lower X-efficiency of the acquiring banks after P&A transactions. In contrast, Cowan et al. (2022), focusing only on deals completed from 2008, take the perspectives of the acquirer's shareholders and show positive long-term market valuation effects. Vij (2020), looking at the acquirer performance and on resolutions from

May 2009, shows negative effects in terms of capital and liquidity, but competitive benefits in the local deposit market. Differently from these previous long-term studies, our analysis jointly focuses on measures of profitability and lending risk as well as capital adequacy, for the combined entity. Thus, our approach places more emphasis than previous studies on the redeployment of failed bank assets rather than the acquirer's shareholders. Importantly, we show that under our empirical setting, we reach the same conclusions when we narrow our attention down to the most recent wave of bank resolutions via P&A deals.

Our work is also related to a more recent stream of research that examines factors that affect the resolution process of failed banks (see Granja et al., 2017; Igan et al., 2022). Granja (2013) show that more comprehensive disclosure requirements in failed banks result in lower costs of closing a bank for regulators and an increase in the likelihood to participate in the bidding by bidders that are geographically more distant. In a related study Granja et al. (2017) document that failed banks are generally sold to bidders that operate in the same county and that share similar business lines. This, however, occurs only when the bidders are well capitalized. It follows that poor capitalization of some potential acquirers drives a wedge between their willingness and ability to pay for failed banks and this wedge drives misallocation. Igan et al. (2022), using a sample of FDIC auctions between 2007 and 2016, document the impact of bank lobbying on the resolution process. While bidding banks that lobby regulators are more likely to win an auction, such auctions lead to larger costs for the FDIC and the resulting acquisitions lead to worse post-acquisition performance than their non-lobbying counterparts. Our heterogeneity tests add further evidence on which factors regulators should expect to be relevant in avoiding the misallocation of resources through the resolution of failed bank assets. In particular, we document the importance of assessing the potential for economies of scale and efficiency gains arising from the deals. In contrast, although business similarity between the target and the acquirer seems to be a critical determinant of the bidding process (Granja et al., 2017), we do not find it plays any benefical role over the long-term for the positive outcome of the deals.

2 The Characteristics of P&A Transactions

P&A transactions are the most widely employed resolution method by the FDIC (see Granja et al., 2017). Compared to other resolution methods, P&A transactions lead to lower costs for the insurance funds (James, 1991) and preserve franchise value (James, 1991). In addition, P&As extend protection to depositors, including the uninsured ones, when all deposits are acquired (Bennett and Unal, 2015), and are more effective in terms of asset liquidation (James, 1991). Finally, P&As are the least disruptive resolution method for local communities (FDIC, 2014).

In a P&A transaction, part or the full amount of bank assets and liabilities are auctioned by the FDIC using a procedure similar to a first-price sealed-bid auction (Giliberto and Varaiya, 1989). The bidding process involves only banks with a regulatory rating indicating limited regulatory concerns, well capitalized banks, and banks with a satisfactory anti-money laundering record (Granja, 2013). The period between the bidding opportunity announcement and the closing of the deal is typically shorter than in ordinary deals (Granja, 2013).

After the release of an information package prepared by the FDIC, and the due diligence by the interested institutions, the bids are submitted. Each bid includes the value of the assets auctioned that each bidder intends to acquire and a premium representing an estimate of the future value of the deposit and loan relationships the bidder will acquire from the failed bank - referred to as franchise value (FDIC, 2013; Walter, 2004). However, most of the time, the amount of the insured deposits the winning bidder assumes with the deal exceeds the value of the acquired assets. Therefore, the acquirer is compensated by a net payment from the FDIC, that is the difference between the value of the deposits assumed and the bid submitted (FDIC, 2013; Walter, 2004).

Since the FDICIA, signed into law in December 1991 in response to the S&L crisis, the resolution can also rely on an SLA between the acquirer and the FDIC. With this agreement some of the losses generated by the assumed assets can be transferred to the insurance fund (Cowan and Salotti, 2015).[4] The loss-split is conventionally based on an 80-20 ratio (namely, 80% is covered by the FDIC). Nevertheless, until March 2010 losses exceeding an established threshold defined in the SLA, were shared according to a 95-5 ratio. Acquirers can assign an asset covered by the agreement a risk-weight that refers to the eligible guarantor (that is, the FDIC) and not the original obligor, thus reducing capital requirements.

The inclusion of the SLA offers the FDIC the opportunity to reduce the risk of disproportionally low bids given the commitment to share future losses. In turn, this creates incentives for the bidder to take assets, that would be otherwise rejected, at a price that is seen as reasonable by the FDIC. Overall, the amount of assets sold with the deal should be higher with the SLA and the ratio of liabilities to assets of the transaction should be lower, and the inclusion of the SLA should encourage bids for P&As with large asset sales (Cowan and Salotti, 2015).

3 Data, Sample and Methodology

3.1 Data and Sample

We construct our sample of P&A transactions using the list of 2,165 deals reported by the FDIC for the period 1984 -2020.[5] From this list, we initially select 1,465 transactions where both the target and the acquirer were commercial banks. We then apply two additional criteria to identify our final sample. First, we exclude P&A transactions for which an unassisted acquisition occurred within the 20-quarter window after the assisted acquisition. To ensure a more representative sample of P&A transactions, we only exclude deals, where another event occurs in the 12 quarters

[4] For full details and changes in the SLA, see https://www.fdic.gov/bank/individual/failed/lossshare/index.html.

[5] To identify commercial banks, we use the Institution Directory provided by the FDIC. We further exclude deals where the acquirer assumes insured deposits only.

leading to an acquisition. Our pre-acquisition window is therefore between 12 and 20 quarters, allowing for the maximum number of quarters that are available before another event takes place. Our purpose is to avoid contamination effects from the occurrence of other (unassisted) deals within the event window.[6] Second, we maintain in the sample only deals for which we have accounting data for both the acquirer and the target from the Consolidated Reports of Condition and Income provided by the FDIC (from the first quarter of 1993) as well as the Federal Reserve Bank of Chicago (for data before the first quarter of 1993).

[Insert Figure 1 here]

Overall, our final sample consists of 475 unique P&A transactions involving U.S. FDIC-insured commercial banks that were completed between 1984 and 2020. Notably, to maintain a highly representative sample of all available acquisitions, we consider as one event those P&A transactions involving the same acquirer that occurred within a one-year window. This choice results in a final number of 429 unique events in the sample.

Figure 1 shows the yearly distribution of all P&A transactions reported by the FDIC from 1984 to 2020 and those in our sample. We capture over 30% of the P&A transactions between commercial banks that occurred in the period of analysis. In Section 4, we document that our results remain unchanged if we increase the number of deals by reducing the event window, thus limiting a possible selection bias.

The number of failures and the number of failed bank acquisitions in the dataset cluster in the period between 1986 and 1992 and in the most recent period between 2008 and 2013. The first period is typically related to the S&L crisis, while the second corresponds to the failure wave

[6] Information on FDIC-insured banks is obtained from www.data.gov, and includes demographic information, operating status, and other key statistics related to the institution. Information on all unassisted mergers was also selected from this dataset.

induced by the GFC as highlighted by Cowan and Salotti (2015). In these two periods we observe 394 acquisitions, equal to nearly 83% of the full sample.

3.2 Methodology

We follow several previous banking and non-banking studies on the effects of M&As and compare the profitability, capital and loan risk of the combined entity between the acquirer and the target banks prior to the acquisition with the profitability, capital and loan risk of the merged banks after the deal (Cornett and Tehranian, 1992; Cornett et al., 2006; DeLong and DeYoung, 2007; Igan et al., 2022; Levine et al., 2020; Papadimitri et al., 2019; Peristiani; 1997; Suk and Wang, 2021). We obtain the pro-forma entity by combining the accounting information of the acquirer and the target in each quarter prior to the acquisition.

The aim of this methodological choice is to offer indications on how the failed bank assets are redeployed and managed. An alternative approach would have been to compare the acquirer profitability, capital and loan risk before the transaction with the profitability, capital and loan risk of the merged entity after the event. However, this alternative approach focuses entirely on the effect of the deal from the perspective of the acquirer's shareholders and would be also less likely than the combined entity approach to capture the synergies due to the combinations of the two banks. For instance, in this latter setting a deterioration in profitability post deal might still be associated with an adequate management of the failed bank assets by the acquiring bank.[7] As discussed in detail in Section 4, we conduct several tests, shown in the Online Appendix, to demonstrate that our findings are not the consequence of any mechanical effects produced by our empirical strategy.

[7] This might occur when the profitability (risk) of the newly bought assets remains below (above) the acquirer's pre-deal level, despite being significantly better than what was observed at the target level.

Using a sample including the combined entities and a restricted matched group of control (non-acquiring) banks, selected following the steps discussed in the next section, we then estimate the fixed effects model reported below, with robust standard errors clustered at the bank level:

$$Y_{i,t}=\beta_0+\beta_1 Post_{i,t} \times Acquisition+\mathbf{BANK}+\mathbf{CONTROLS}+\mathbf{QUARTER}\times\mathbf{STATE}+u_{i,t} \qquad (1)$$

Where $Y_{i,t}$ is a profitability/capital/loan risk measure depending on the specification we estimate, $Post_{i,t}$ is a dummy taking a value of one for the period after an acquisition and *Acquisition* is a dummy equal to one over the sample period for an acquirer-target combined entity. The interaction $Post_{i,t}\times Acquisition$ measures the changes in the dependent variable of the combined entity after the acquisition relative to the change we observe in the control group, **BANK** is a vector of bank fixed effects, **CONTROLS** is a vector of bank characteristics, and **QUARTER×STATE** is a vector of quarter-state fixed effects that accounts for time variant state variables that might affect bank outcomes in the local market.[8] More precisely, we estimate the model on an acquisition event dataset around P&A transactions. We employ an event period of up to 40 quarters around each event date and then stack together the different event windows we have constructed for each transaction.

We use three dependent variables. The first is a profitability measure based on the ratio between net income and total equity (**ROE**). This measure is used, for instance, in Cornett and Tehranian (1992) and Cornett et al. (2006) in the context of unassisted bank M&As. Being an indicator of bank performance from the perspective of shareholders, it allows us to offer complementary information to the evidence on wealth transfer and value creation reported in short-term event studies on P&A deals. The second variable is the ratio between equity and total assets (**Capital**) as

[8] We define the state dummies based on the headquarter location of the acquirer. However, employing location dummies based on the target does not have any effect on our results. Additionally, we our results remain unchanged if we focus on single state deals.

in Cornett et al. (2006) and Vij (2020). This variable is particularly important in the context of P&A deals, as the regulatory requirements in the bidding process privilege better capitalized banks (Granja et al., 2017), while the target is expected to show a deteriorated capital adequacy at the time of the deal. As a result, it is ex-ante unclear how the capital position of the combined entity is expected to evolve after the deal. The final dependent variable is a measure of asset quality based on non-performing loans divided by total loans (**NPL**). This measure gives indications on whether the combined entity indeed results in an improved credit risk management practice. This would be consistent with the presence of a superior management team acquiring the failed bank assets as implied by the strict requirements imposed on acquirers for being involved in the bidding process.

The controls are lagged by two quarters to mitigate endogeneity concerns (Spokeviciute et al., 2019)[9]. However, our results hold if we employ alternative lags as documented in Section 4.3. We account for differences in bank business models via the ratio between real estate loans and total loans (**RE Loans**), the ratio between commercial and industrial loans and total loans (**CI Loans**), and the ratio between consumer loans and total loans (**Consumer Loans**). Additionally, we control for the log of bank total assets (**Size**), deposits divided by total assets (**Deposits**), the ratio between liquid assets and total assets (**Liquid Assets**), and a proxy for bank (in)efficiency based on the ratio between non-interest expense and the sum of net interest margin and non-interest income (**Inefficiency**). Notably, when the denominator of any of the flow variables employed in the analysis is taken from the balance sheet (stock variable), similarly to Igan et al. (2022), we employ its average computed over two quarters to construct the related measure.

3.3 The Selection of the Group of Non-Acquiring Banks

[9] We further motivate the choice of two lags as it ensures data for the target before the failure is available. Specifically, for nearly 15% of the total P&A transactions the earliest available data is two quarters prior the acquisition.

The combined target-acquirer entities could exhibit characteristics that are inherently different from those of non-acquiring banks. Including, therefore, all non-acquiring banks in the analysis might bias our results due to omitted control variables (only partially captured by the inclusion of bank fixed effects). To mitigate this concern, we match the combined entity with non-acquiring banks on several characteristics observed before the deal using Propensity Score Matching (PSM).[10]

We begin the matching process by selecting the potential control and treated samples. The former includes all banks that do not fail and do not acquire a failing bank throughout the sample period, whereas the latter includes all commercial bank P&A transactions. When a bank acquires more than one failing bank in the same quarter, we assume it as one P&A transaction.

To estimate the propensity scores, we run a logit model wherein the dependent variable is the event of a failed bank acquisition, and the explanatory variables consist of a set of bank-specific determinants, including most of the performance measures we employ as the outcome variables in equation (1). More precisely, the explanatory variables include the share of RE loans, CI loans and Consumer Loans in the loan portfolio, Size, Deposits, Capital and NPL.

Additionally, we account for geographic proximity by matching the combined entity only with potential control banks in the same Federal Reserve District. We do not match by state for two reasons. First, we observe that a tighter geographic matching reduces significantly the number of potential control banks and the related matching quality. Second, acquirer and target might occasionally be in different states, and this makes a tighter geographic matching problematic. We further restrict the matching process to include control banks in the same size group (4 distinct size quartiles of the sample distribution) and by quarter. The direct matching by time should reduce the impact of macroeconomic factors on our results.

[10] For a similar approach to reduce heterogeneity between treated and control groups, see He et al. (2020).

We select up to 5 non-acquiring banks for each pro-forma combined entity using the nearest neighbor matching algorithm with replacement. After ensuring the requirement of common support (namely, that banks with the selected characteristics have a positive probability of being in both acquiring and non-acquiring groups (Caliendo and Kopeinig, 2008)), the above process matched 422 distinct pro-forma banks (involved in 429 unique events) with 1,728 distinct control banks.

Panel A of Table 1 shows summary statistics for the two groups of banks before the matching, while Panel B shows the same statistics for the two groups after the matching. Panel A shows the two groups of banks are different across all characteristics before the matching. However, after the matching the two groups are extremely similar. The mean equality tests, reported in Panel B, show no significant differences between the average bank characteristics of the two groups.

[Insert Table 1 here]

Our final sample consists of approximately 73,000 observations. Table 2 reports summary statistics for the sample. Banks in the sample show average positive performances and an average degree of capital strength of about 8.4%. These banks raise most of their funding in the deposit market and their business focus consists of providing loans.

[Insert Table 2 here]

4 Baseline Results

4.1 Long-term Effect of P&A Transactions

The first three columns of Table 3 present the results of equation (1). The overall picture is that such acquisitions lead to benefits for the combined entity at least in terms of profitability and loan risk, while they do not affect its capital adequacy. Following Mitton (2024) we estimate the economic importance of our results by scaling the estimated $Post_{i,t} \times Acquisition$ coefficient by the standard deviation of the dependent variable. Following this approach, we find that ROE (NPL) for the combined entity increases by 0.36 (0.23) standard deviations post-acquisition, as compared to the non-acquiring banks.

In terms of control variables, we find that larger banks show lower performance and higher risk. The former result is consistent with earlier evidence reported in Berger et al. (1987) and reiterated by Saghi-Zedek and Tarazi (2015). Furthermore, the fact that large banks benefit from implicit and explicit bailout guarantees may justify their larger risk exposure (Laeven et al., 2016). We also find that banks with higher deposits show better profitability and higher loan risk. This is consistent with lower cost of funding associated with deposit-taking and lower monitoring from (insured) depositors (Demirgüç-Kunt and Huizinga, 2004). The results for the different lending shares suggest that increases in the lending focus of a bank in one specific category improves profitability and lowers risk, consistently with recent evidence on the importance of lending specialization (see, for instance, Blickle et al., 2023; Paravisini et al., 2023). Finally, more inefficient banks show lower profitability, less capital and higher risk (see Fiordelisi et al., 2011, for similar results).

[Insert Table 3 here]

As discussed previously, the most recent period with the largest number of deals ranges from 2008-2013. Cowan and Salotti (2015) show that winning bidders realize substantial positive abnormal stock returns during this period and interpret this finding as indicating wealth transfer from the FDIC to acquirer shareholders. Furthermore, the bank failures in this period are largely the consequence of the GFC. Granja et al. (2017) highlight large costs for the FDIC during this crisis from the resolution of failed banks and potential distortions in resource allocation that might arise when acquirers are poorly capitalized.

None of the studies above, however, show long-term evidence for the most recent wave of P&A deals and document whether this period reflects more general dynamics observed over the full sample. We focus on these aspects and examine if the failure events occurring around the 2008-2013 period offer a different picture from the full sample tests. Accordingly, we repeat the analysis only for deals completed during this period. We report the results of these additional tests in the last 3 columns of Table 3. We do not observe noticeable differences with respect to the full sample results when we focus the analysis on the acquisitions that cluster in the period 2008-2013.

In summary, our results highlight that the deals never resulted in negative effects for the combined entity. Instead, they tend to produce positive effects over the longer-term.

4.2 Long-term Effect of P&A Transactions: A Dynamic Approach

An obvious follow-up question is whether the highlighted positive effects materialize beyond the shorter-term and consistently over time. Alternatively, they might emerge with a specific time dynamic and require several years to be realized. To address this question, we create 20 interaction terms with *Acquisition* by using 20 different dummies for each quarter after the completion of the transaction. Therefore, this approach allows us to highlight the evolution of the dependent variable in the acquirer sample relative to the matched sample after the completion of the deal. To ease exposure and the interpretation of our results, we plot the coefficients and the corresponding 95% confidence intervals in Figure 2.

[Insert Figure 2 here]

This additional setting shows that the profitability gains, although persistent, seem to be decreasing over time. We achieve a similar conclusion if we focus on the evolution of the NPL; namely, the benefits in terms of decreases in NPL tend to materialize especially in the first part of the post deal period. The figure also suggests that the lack of impact of the capital strength of the combined entity is primarily due to a negative effect in the immediate period following the deal that is absorbed over time.

Overall, taken together the findings discussed in this and the previous section, we observe that our evidence is in sharp contrast with some earlier long-term evidence (see Peristiani, 1997). We document that any negative effect is extremely limited and short-lived. By contrast, significant benefits for the combined entity generally emerge over the longer-term.

4.3 Additional Tests

Admittedly, attaching a causal interpretation to the results presented in the previous section is problematic. For instance, it might be suggested that the outcome we observe is not different from what we would have found for any other combination of banks. Therefore, to further understand, if there is indeed any specific effect generated by P&A acquisitions as compared to other forms of business aggregation outside the regulatory oversight, we repeat the analyses by relying on a different matching strategy.

Specifically, we match the combined entity prior to a P&A transaction to a combined entity obtained for a bank acquisition undertaken outside the P&A resolution framework. If what we are capturing in the previous section is a general acquisition effect unrelated to any specificity of the resolution arising from P&A transactions, our results should vanish under this alternative matching strategy. In the Online Appendix (columns from (1) to (3) of Table A1), we show this is not the case. We still observe that our findings hold; that is, business aggregations via P&A transactions deliver better profitability and positive risk effects post-acquisition than other forms of bank consolidation involving comparable combined entities, although there is no difference in terms of bank capital.

Another possible concern is that our matching strategy compares an aggregation of banks in the P&A group with an individual entity in the control group and this might mechanically generate some of our results independently of the P&A deal. Therefore, rather than constructing the control group by directly matching the combined entity with non-acquiring banks, we match separately the target and the acquirer to similar banks as in Ghosh (2001). We then compare the evolution of profitability, capital and risk of the combined entity from the P&A to that of the combined entity for the matched pair of banks. To implement this test, we follow the same matching strategy discussed in Section 3.3. Our prior here is that if our results are only the consequence of our aggregation strategy of accounting data prior to the deal without any added value stemming from the P&A transaction, we should find they vanish under this alternative matching strategy. In the Online Appendix (columns from (4) to (6) of Table A1), we document that under this alternative empirical setup our results tend to be generally consistent with our initial evidence.

It might also be argued that the selection of 5 banks in the control group for each combined entity, does not remove enough heterogeneity between the two groups of banks and drives our results. Therefore, we repeat the main analysis by selecting only 1 control bank for each combined entity. Using this alternative matching strategy our results remain unchanged (see the last three columns of Table A1).

We next address three further methodological concerns. First, bank outcomes can be correlated across states, thus requiring clustering at the geographic level. However, we show in Table A2 that clustering by state has no material effects on our results. Second, the choice of two lags for the controls may be seen as rather ad-hoc. We show in Table A3 that under alternative lag choices, our results remain unchanged. Third, the focus on a very long event window, and the consequent selection criteria, may determine a significant selection bias. In Table A4, we mitigate this concern by repeating the analysis using an event window equal to and (-3, +3) years. This increases the number of deals to 513 but leaves our results unchanged.

Finally, to further confirm our results are capturing the impact of P&A transactions, in Table A5 of the Online Appendix we present a falsification test wherein we randomly allocate acquisition dates across acquirers. Under this setting, none of the significant effects in our baseline results are confirmed.

5 Sources of Heterogeneity in P&A Results

In this section we test for the presence of source heterogeneity in our results. In doing so, we differentiate factors which have been identified as relevant drivers of performance in unassisted M&A deals from factors that are peculiar to the structure of P&A transactions.

5.1 Non- P&A Specific Factors

In the following three sub-sections, we discuss factors that have been typically identified as key drivers for the success of unassisted M&As in the banking industry.

5.1.1 Economies of Scale

One of the conventional arguments that is generally used to motivate performance changes from M&As is the possibility that the combined entity reaches scale economies (see, among others, DeLong, 2003; DeYoung et al., 2009; Humphrey and Vale, 2004; Peristiani, 1997). Such economies are the result of a decrease in the average production cost due to the bigger production scale following the increase in bank size after the deal.

Nevertheless, it is also suggested that the observed increase in size may lead to diseconomies when it increases within-firm transaction costs because of more organizational complexity (DeLong, 2003). Additionally, more diversification induced by a larger scale can generate additional risk-taking incentives that also lead to diseconomies of scale (Hughes and Mester, 2013). Both the arguments in favor and against economies of scale can potentially hold in the context of P&A transactions. Indeed, these transactions may significantly affect the production scale of banks, especially if the increase in bank size observed for the combined entity is substantial.

In this section, we examine the importance of economies of scale on our results by following a similar approach as in DeLong (2003). We construct a measure of the relative size of the deal based on the total assets of the target scaled by the total assets of the acquirer. We next partition our P&A sample into large and small deals if the relative size ratio is above (below) the last (first) quartile of the M&A sample distribution and interact the related dummies with the post dummy. In other words, we introduce in the model two interaction terms: $Post_{i,t} \times Small\ Relative\ Size_i$ and $Post_{i,t} \times Large\ Relative\ Size_i$. Therefore, the setting we follow resembles the approach in Irani and Oesch (2013; 2016) to identify source of heterogeneity within the group of "treated firms". This portioning approach is needed when the variable employed to differentiate firms is only observable, as in our case, for treated firms. If economies of scale matters for the positive outcome of the deals, we should observe better performance gains for relatively larger deals (DeLong, 2003); that is, when the target is relatively larger.

[Insert Table 4 here]

We report the regression results of this analysis in Panel A of Table 4, while in Panel B we test if the difference in our results by relative deal size is statistically significant at conventional levels. We find evidence consistent with the positive arguments on the importance of economies of scale proposed in the context of unassisted M&A deals. We document significant improvements in terms of profitability and risk only in relatively larger P&A transactions. This finding suggests that the positive outcome of P&A deals is significantly affected by the potential to achieve economies of scale with the transaction.

5.1.2 The Potential for Efficiency Gains: Efficiency Gap Between the Target and the Acquirer

The transfer of skills between the acquirer and the target is potentially another key driver of the success of unassisted M&As (DeLong, 2003). For instance, Berger and Humphrey (1992) and Hannan and Pilloff (2009) show that acquirers tend to be significantly more efficient than targets.

This is interpreted as an indication that the acquirer can have the ability to improve the efficiency of the target. However, DeLong (2003) does not find strong support for a nexus between long-term performance and the difference in efficiency between the acquirer and the target.

In the case of P&A transactions, the relative efficiency argument can be particularly pertinent given that the regulatory requirements imposed on acquirers should bias the deals towards acquirers with better skilled managerial teams. We test the relative efficiency hypothesis in the first three columns of Panel A of Table 5, where we replicate the empirical setting of the previous sub-section by separating deals with low and high efficiency gaps between the target and the acquirer. These efficiency gaps are based on the difference between the inefficiency ratio of the target and the inefficiency ratio of the acquirer (computed as described in Section 3). Next, in Panel B we formally test if the differences in our results by degree of relative efficiency is statistically significant at conventional levels. Across all models, we observe that acquisitions deliver better long-term performance when the target is much more inefficient than the acquirer.

[Insert Table 5 here]

5.1.3 Business and Geographic Overlaps

Granja et al. (2017) document that acquirers in P&A transactions seem to privilege targets that share more similar business models with them. Intuitively, this choice might be justified by the expectation that more business overlaps might contribute to generating synergies and cost savings for the acquiring banks with consequently better outcomes from the deals. Nevertheless, it could be also argued that less business overlap can generate potential advantages for acquirers to the extent to which this can facilitate diversification and business expansion in new areas (Hoberg and Phillips, 2010).

To understand if business overlaps between the acquirer and the target influence our results, we construct a Jaccard loan portfolio similarity measure following Fricke (2016). Pool et al. (2015)

employ a similar measure in the context of measuring overlaps among stock portfolios of mutual fund managers. We build our index by focusing on the following loan categories for the acquirer and the target as in Lee et al. (2024): a) construction and development loans, b) farmland loans, c) residential loans, d) multifamily residential loans, e) commercial real estate loans, f) non-residential loans held in foreign offices, g) loans to depository institutions and acceptances of other banks, h) commercial and industrial loans, i) agricultural loans, j) credit card loans, k) other loans to individuals, l) loans to foreign governments and official institutions, m) lease financing receivables and n) other loans. The last category (other loans) is defined as the difference between total loans and the sum of the other thirteen categories. We then estimate the following measure of similarity:

$$\text{Loan\_Similarity}_{A,TA}^{t} = \frac{\sum_{k=1}^{K} \min\left(w_{A,k}^{t}; w_{TA,k}^{t}\right)}{\sum_{k=1}^{K} \max\left(w_{A,k}^{t}; w_{TA,k}^{t}\right)} \tag{3}$$

Where $w_{A,k}^{t}$ and $w_{TA,k}^{t}$ are the shares of type of loans *k* in the total loan portfolio of the acquirer A and the target TA, respectively, in quarter *t* prior to the acquisition. Larger values of the index indicate that the loan portfolio of the two merging banks were more similar prior to the completion of the deal. As in the previous tests, we next repeat our empirical investigation by partitioning the sample of transactions into low and high degree of loan similarity. We identify as characterized by a low (high) degree of overlaps those deals where our overlap measure is below (above) the first (last) quartile of the sample distribution.

[Insert Table 6 here]

We present the results of these regressions models in the first three columns of Panel A of Table 6, whereas in Panel B we formally test if the differences in our result by degree of business similarity is statistically significant at conventional levels. We do not find our results vary with the degree of business overlap.

A closely related aspect that can affect the outcome of the acquisition is its geography, and in particular the network overlap between the target and the acquirer. Granja et al. (2017) observe that geographic proximity is an important determinant of the bidding process. However, as in the case of business similarity, the impact of the degree of geographic overlap is ex ante unclear (see, Levine et al., 2020).

On the one hand, high overlap deals can facilitate cost savings and lead to an increase in market power after the deal, with a consequent benefit in terms of bank performance. Along these lines, Houston and Ryngaert (1994) and DeLong (2001) show that the market responds positively when the target and the acquirer share geographic overlap. Similarly, Cornett and Tehranian (1992) document that intrastate mergers result in greater improvement in long-term performance than interstate performance. On the other hand, high overlap deals can lower risk diversification benefits, with the effect to increase a bank's cost of capital, reduce the efficiency of financial intermediation and impede the governance of the bank as compared to deals with low geographic overlap (Goetz et al., 2016; Levine et al., 2021). The risk diversification argument can be potentially pivotal in the case of P&A transactions as they are designed for the takeover of highly risky targets.

To understand if any of the above arguments hold in our sample, we follow a similar approach as for the analysis based on loan portfolio similarity and start by constructing the branch network overlaps per state between the target and the acquirer based on yearly branch data taken from the Summary of Deposits (SOD) provided by the FDIC. The measure is the minimum between the number of branches reported by the target and the acquirer in a state, aggregated across different states and scaled by the sum of the maximum number of branches of the acquirer and the target prior to the deal in each state as follows:

$$\text{Branch\_Similarity}^{t}_{A,TA} = \frac{\sum_{j=1}^{J} \min\left(\omega^{t}_{A,j};\omega^{t}_{TA,j}\right)}{\sum_{j=1}^{J} \max\left(\omega^{t}_{A,j};\omega^{t}_{TA,j}\right)} \quad (4)$$

Where $\omega^t_{A,j}$ and $\omega^t_{TA,j}$ are the number of branches in a state j for the acquirer A and the target TA, respectively, in quarter t prior to the acquisition. We next repeat our empirical investigation by partitioning the sample of transactions into high and low degree of branch overlaps. We identify as characterized by a low (high) degree of overlap those deals where our overlap measure is below (above) the first (last) quartile of the sample distribution.

The results, reported in the last column of Panels A and B of Table 6 are mostly consistent with the evidence shown for business overlap; namely, we do not find generally that our results depend on the degree of geographic overlap between the branch networks of the acquirer and the target. The only exception being the presence of marginally larger profitability gains in deals with a high degree of branch network overlap between the acquirer and the target. Notably, our findings on the role played by geographic overlaps are not in line with the evidence reported by Levine et al. (2020) for unassisted bank M&As, wherein geographic diversification seems to be beneficial for the outcomes generated by the deals.

5.2 P&A Specific Factors

We next move to the investigation of the importance of P&A specific characteristics on our results. In this respect, a first factor that can influence our findings is the presence of an implicit regulatory subsidy in favor of the acquirer as reflected by resolution costs. A second factor we examine is the presence of an SLA.

5.2.1 Do Resolution Costs Matter?

FDIC incurs significant resolution costs that are generally defined as the difference between the liabilities of the failed bank and the market value of its assets after the deduction of expenses (Bennett and Unal, 2015). These costs include losses incurred on the disposition of the assets of the failed bank, direct expenses, and indirect expenses to resolve bank failures. Bennett and Unal (2015) suggest that total resolution costs are also a proxy for the market value of equity assigned to the failed bank.

We collect failed bank resolution costs from the FDIC website and based on previous studies (see, for instance, Granja et al., 2017; Kang et al., 2015) we adjust the costs by the failed bank's total book value of assets. All failed bank costs and total book value of assets are consolidated by each deal, as defined in Section 3. We partition the acquisition sample into two groups: 1) low-resolution cost acquisitions where the adjusted value of costs falls into the first quartile of the sample distribution; 2) high-resolution cost acquisitions which are in the last quartile of the sample distribution. We then re-estimate our baseline model by interacting the dummies identifying the two groups with the post dummy. The first three columns of Panel A of Table 7 present the regression results of this test and Panel B shows whether the difference in performance between the two groups of deals is statistically significant.

[Insert Table 7 here]

We find some evidence that deals with high resolution costs for the FDIC result in a stronger improvement in the degree of profitability. However, there is no evidence that the magnitude of the resolution costs matters for the capital and loan risk effect of the deals.

Overall, it seems that the costs faced by the FDIC, and the related subsidy obtained by acquirers, marginally amplify the positive profitability outcomes of the deals. Nevertheless, it also appears unlikely these costs are good predictors of the outcome of the P&A transaction.

5.2.2 SLA versus Non-SLA deals

It has been suggested that the SLA can induce acquiring banks to bid for riskier targets, with the effect of potentially mitigating the positive outcome of the deal. However, the agreement also aims to reduce losses for the acquirer with potential performance benefits. Along these lines, Cowan and Salotti (2015) document that acquirers pay more for targets when there is an SLA attached to the transaction. However, isolating the effects of an SLA in a deal is extremely challenging due to endogeneity. SLAs are not randomly assigned and some transactions might be more likely to be accompanied by such agreements, and thus intrinsically different from those without an SLA. In particular, the characteristics of the target and the acquirer and systemic conditions might influence the SLA adoption. Indeed, as documented in the Online Appendix, the average characteristics of the combined entity in the SLA and non-SLA groups are different across several dimensions.[11]

We attempt to account for these aspects through two methodological steps. Although individually each step might not be sufficient to remove endogeneity issues, jointly they can, at a minimum, significantly mitigate these issues.

First, we start by selecting only the years in our sample where we have information on the inclusion of an SLA in a transaction (this period ranges from 2008 to 2013). For these years, we then identify another group of deals without SLAs. Matching by time allows us to mitigate the potential effects of confounding factors that would emerge by comparing SLA deals with non-SLA deals completed over a different period. Examples of such factors could be, for instance, differences in the business cycles of local economies or in systemic conditions.

Second, we mitigate differences in bank characteristics between the two groups of deals, by identifying a smaller number of SLA deals and non-SLA deals that share more similar characteristics. To this end, we use a 1 to 1 propensity score matching between SLA and non-SLA deals. The matching is based on the same variables used in Table 1 for our initial matching strategy and leads to a final matched sample of 45 SLA acquisitions and 45 non-SLA acquisitions.

We next move onto the examination of the impact of SLA deals. In the last three columns of Table 7 we compare the outcome of SLA deals versus the outcome of non-SLA using the matched sample of non-SLA. We observe that the presence of SLA deals results in only a marginal

[11] As shown in Table A6 of the Online Appendix, SLA deals are larger, in line with the regulatory aim to stimulate bids for larger deals, have higher share of non-performing loans of the combined entity, but lower share of CI loans.

difference between the two groups of deals in terms of profitability outcome; that is, we find a larger profitability improvement when the deal is characterized by the presence of an SLA. Additionally, the lack of any difference in the risk and capital outcome of the deal does not confirm the view that SLA might induce acquirers to be overly optimistic in their bids for riskier targets.

The results in this section highlight a marginal influence of SLAs on the outcome of the resolution process of failed banks based on P&A transactions. Furthermore, jointly with the evidence from the previous test, the results of the SLA analysis show that P&A specific factors do not entirely explain our findings.

5.3 Heterogeneity Across Deals Completed in High and Low Failure Intensity Markets

In the model of Acharya and Yorulmazer (2008), when bank failures are particularly numerous, we observe an increase in the volume of assets to liquidate and simultaneously liquidity constraints in surviving banks. The outcome is a sub-optimal liquidation process since failed bank assets are more likely to be acquired by inefficient users that do not have liquidity problems. It follows that P&A transactions should lead to better outcomes when the number of bank failures in a market is relatively smaller. The consequence, therefore, would be that the resolution process would be less effective in ensuring the redeployment of bank assets, when the resolution is more needed (that is, when systemic conditions are more deteriorated given the large number of bank failures). Acharya and Yorulmazer (2008) argue that this may induce regulators to subsidize deals during crisis periods.

To understand if the argument above finds some support in our sample, we identify the number of bank failures in a local market, defined at the state level, at the time of completion of each deal. To this end we use information on bank failures from the FDIC. In line with the framework of Acharya and Yorulmazer (2008), we then construct a proxy for intensity of bank failures at the completion date of each deal through the ratio between the number of failed banks in a state and the total number of banks in the same state. Notably, we use the state of the acquirer in the analysis. Therefore, under the theory framework of Acharya and Yorulmazer (2008), we are assuming that other potential acquirers of the target would have been in the same state of the winner of the bidding process. Nevertheless, our results are not affected if we define the failure intensity using the state of the target or the combined information for the state of the target and the acquirer.

Using the ratio described above, we classify deals announced in periods of high failure intensity in a local market as those that are in the last quartile of the failure intensity distribution, and deals of low failure intensity periods as those in the first quartile of the failure intensity distribution.

Finally, we introduce in our baseline model two interaction terms: $Post_{i,t} \times Low\ Failure\ Intensity\ Deals_{s,t}$ and $Post_{i,t} \times High\ Failure\ Intensity\ Deals_{s,t}$. Therefore, these interaction terms capture the evolution of the profitability, capital and loan risk of the combined entities for events occurring in periods of low and high failure intensity in local markets, respectively.

[Insert Table 8 here]

We report the results of this analysis in Table 8. We do not find any evidence that deals completed when the share of bank failures in the local market is higher leads to worse outcomes. Furthermore, in the Online Appendix (Table A8), we show that the lack of difference we have observed between deals announced during periods of low and high failure intensity is not driven by a sub-set of deals in our sample.

Specifically, we begin by excluding deals involving large acquirers (that is, those on the top quartile of the size distribution). Here the possibility is that during periods of high failure intensity, regulators encourage deals especially by large acquirers that may have better skills and capacity to manage the deals. Next, we exclude from the sample acquirers with high liquidity that in the model of Acharya and Yorulmazer (2008) should drive negative outcomes. In such a case their exclusion should lead to observe better deal outcomes during low intensity failure periods. We next exclude deals based on a very high degree of business or/and geographic overlap between the acquirer and the target. The possibility here is that the benefits of high strategic complementarities may emerge at least during periods of high failure intensity when local market are more turbulent. In such a case the removal of these deals should lead to observe results more in line with Acharya and Yorulmazer (2008). Finally, we exclude deals, where the costs to the regulator are very high. In the theoretical predictions by Acharya and Yorulmazer (2008) the regulators may intervene to provide subsidies to avoid misallocation. We, therefore, could find evidence of worse performance in high failure intensity periods when we remove the effects of these subsidies. None of these tests, however, seems to indicate that a particular sub-set of deals affects the results in Table 8.

[Insert Table 9 here]

One potential limitation of the tests above is the fact that they offer only indirect evidence on the stability consequences of the deals under periods of different failure intensity. Instead, it may be argued that the stability consequences are those that really matter for regulators especially during periods of high failure intensity as they affect systemic stability.

Table 9 accounts for the critique above by repeating the analysis using as a dependent variable a proxy for bank default risk, a bank's z score (Fiordelisi and Marques-Ibanez, 2013).[12] We begin in column (1) of Table 9 by estimating a baseline model as those in Table 3 that we employ as a benchmark regression. We find that the deals result in stability benefits; that is, the default risk of the combined entity decreases after the deal relative to the control group. In the second column,

[12] We compute the bank z-score using a ratio between the sum of Return on Assets (ROA) and Capital ratio and earnings volatility, measured as a standard deviation of ROA over four quarters.

we show that this result holds also when the control group consists of unassisted M&A in the banking industry. This suggests that the resolution via P&As may be more effective than any private solution via M&As. Finally, in the last column we repeat the analysis by separating low and high failure intensity periods as defined in our initial tests. Again, we do not find any evidence of misallocation of resources in periods of high failure intensity. By contrast, we observe that the stability benefits from the deals emerge in these periods; namely, when these benefits are more needed from a systemic perspective.

Overall, our findings indicate that the degree of failure intensity in local banking markets does not lead to worse outcomes in P&A transactions.

6 Conclusions

The resolution of failed banks via auctions by the FDIC may generate significant costs for the deposit insurance fund (Granja et al., 2017). However, this resolution method is also expected to offer benefits by maintaining the failed bank in place with the potential to preserve the value of failed bank assets and the relationships with clients. In this study we use a matched-sample approach and panel fixed effect models to document that the highlighted expected benefits are reflected in some long-term positive effects for the combined entity following the deal. We show that bank resolution via assisted acquisitions through the FDIC leads to a significant increase in the profitability and a decrease in loan risk of the combined entity after the completion of the deal.

We next examine what drives the outcome of the deals and observe that some conventional factors identified in the literature as potential drivers of long-term performance in unassisted M&As also matter in the context of P&A deals. Specifically, we find evidence consistent with a role for economies of scale and efficiency improvements but not any from synergies due to business overlaps between the acquirer and the target and marginal profitability gains from geographic overlaps.

In contrast to the evidence on the importance of non-P&A specific factors, we document that P&A specific factors, such as the implicit subsidy offered by the FDIC via resolution costs and the inclusion of an SLA, influence the profitability of the combined entity but not other deal ountomes. Similarly, in contrast to theoretical predictions, we do not find that a larger share of bank failures in the local market affects the long-term outcomes of the P&A deals.

Ultimately, the results presented here are the first to document how the long-term benefits materialize across different dimensions and can be affected by non-P&A and P&A specific features surrounding the resolution process. Overall, our work shows that a proper assessment of the costs of the resolution process for the FDIC should properly account for the longer-term benefits of the transactions we have documented.

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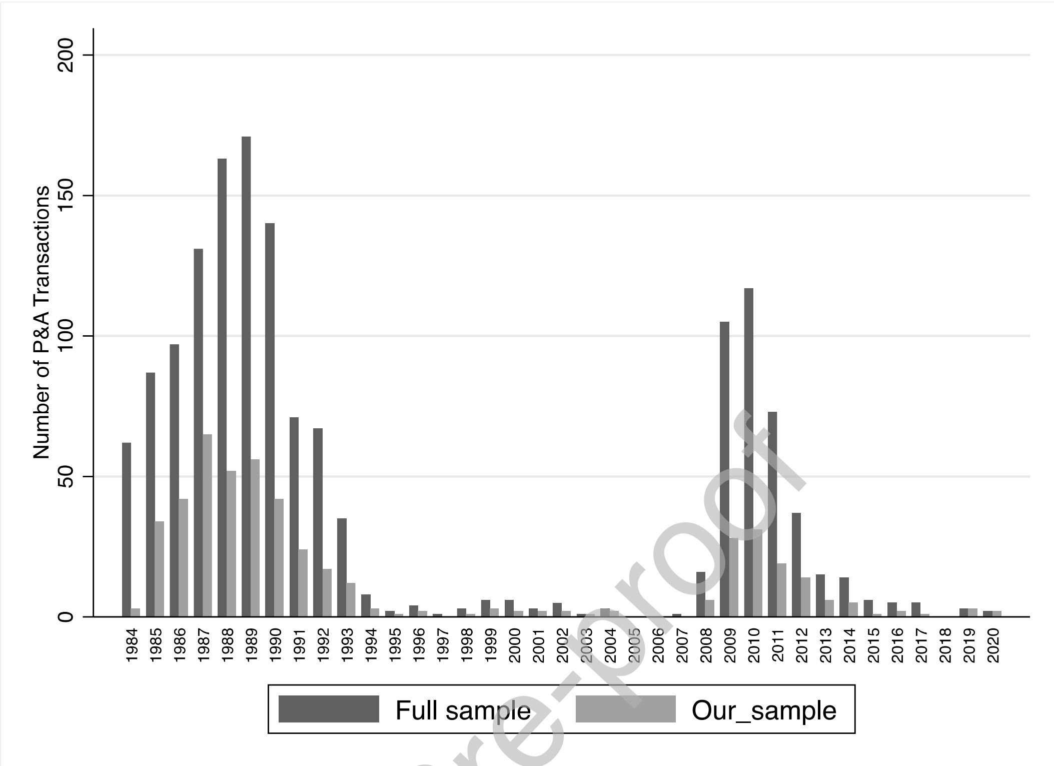

Figure 1. Sample Distribution of U.S. Government Assisted Failed Commercial Bank Acquisitions, 1984-2020

This figure shows the sample distribution of government assisted failed bank acquisitions of US commercial banks between 1984 and 2020. The black columns show the distribution by year for the total number of failed bank acquisitions, where both the acquirer and the target are commercial banks (a total of 1,465 acquisitions). The grey columns show the sample distribution by year for the acquisitions included in our study (a total of 475 acquisitions, i.e., 32% of the total number).

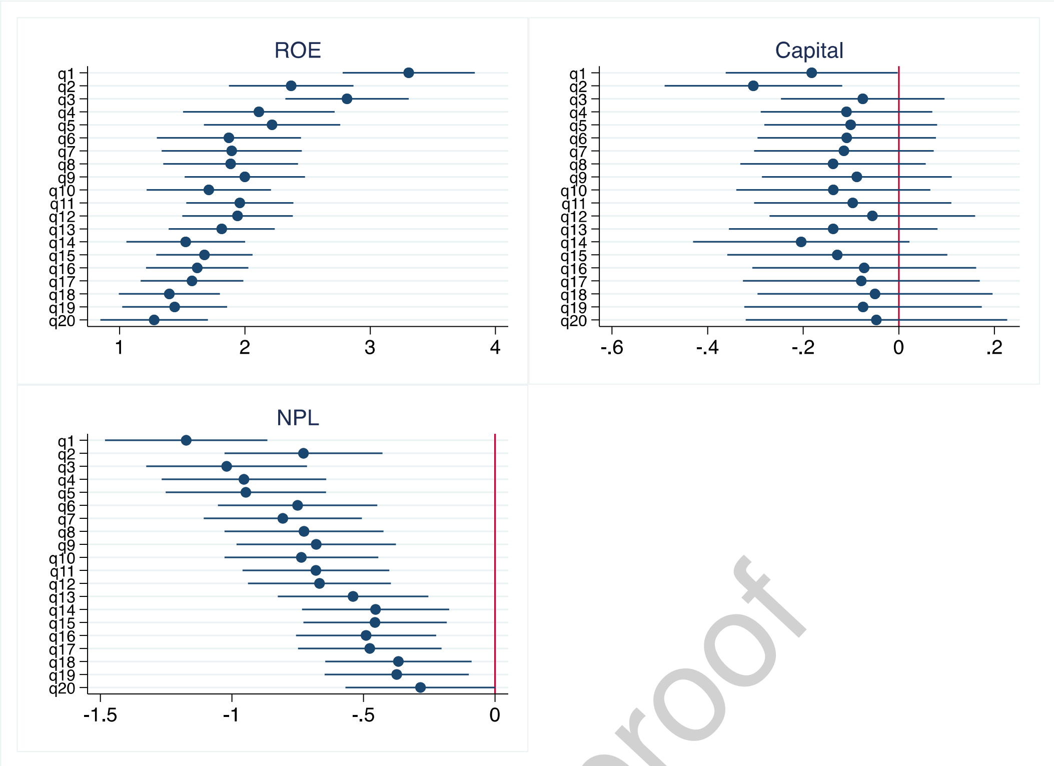

Figure 2. Quarterly Failed Bank Acquisition Effects on ROE, Capital and NPL

This figure shows the 5-year quarterly failed bank acquisition effects on acquirers' ROE, Capital and NPL. The circles represent the coefficient values, and the spikes are 95% confidence intervals of the unreported dynamic effects regressions (see Section 4.2 for details). The red vertical lines represent the reference lines of coefficients equal to 0.

Table 1. Propensity Score Matching

This table reports the results of propensity score matching tests. Panel A shows the results for the non-matched sample and Panel B shows the results for the matched sample. The means for the non-acquiring banks and the combined entity are reported in Columns (1) and (2), respectively. The mean difference (Columns (2)-(1)) and the corresponding t-statistic are reported in Columns (3) and (4), respectively. **RE Loans** is the ratio between real estate loans and total loans. **CI Loans** is commercial and industrial loans divided by total loans. **Consumer Loans** is consumer loans scaled by total loans. **Size** is the natural logarithm of the total book value of assets in real terms in thousands of US$. **Deposits** is total deposits divided by total assets. **Capital** is total book equity scaled by total assets. **NPL** is non-performing loans divided by total loans. All variables are lagged by two quarters. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1) Non-Acquiring Banks	(2) Combined Entity	(3) Difference in Means	(4) t-stat
Panel A. Means and univariate tests before the matching				
RE Loans$_{t-2}$	52.070	49.290	2.780***	2.724
CI Loans$_{t-2}$	17.750	22.954	5.204***	9.271
Consumer Loans$_{t-2}$	16.141	14.907	1.234**	2.041
Size$_{t-2}$	11.457	12.417	0.960***	16.858
Deposits$_{t-2}$	86.149	88.365	2.216***	5.846
Capital$_{t-2}$	9.884	7.472	2.412***	13.670
NPL$_{t-2}$	1.967	5.682	3.761***	34.044
Panel B. Means and univariate tests after the matching				
RE Loans$_{t-2}$	49.402	49.290	0.111	0.096
CI Loans$_{t-2}$	23.830	22.954	0.876	1.307
Consumer Loans$_{t-2}$	15.174	14.907	0.266	0.423
Size$_{t-2}$	12.321	12.417	0.096	1.401
Deposits$_{t-2}$	88.629	88.365	0.264	0.941
Capital$_{t-2}$	7.542	7.472	0.069	0.603
NPL$_{t-2}$	5.459	5.682	0.223	1.144

Table 2. Summary Statistics

This table presents descriptions and summary statistics of the variables used in the empirical analyses. The dependent variables are presented in Panel A while the independent variables are presented in Panel B. The summary statistics are provided for the five-year pre- and post-acquisition window sample used in the main empirical tests and as they enter the empirical analyses (the independent variables are lagged by two quarters). All variables, except Post×Acquisition and Size, are winsorized at the 1% level.

VARIABLES	(1) Definition	(2) N	(3) Mean	(4) p50	(5) S. Dev.	(6) p1	(7) p99
Panel A. Dependent Variables							
ROE	The ratio between bank net income and average of total equity at quarter *t* and *t-1* (%).	73,210	1.507	2.618	5.548	-22.942	9.846
Capital	Book value of equity divided by total assets (%).	73,210	8.430	8.125	2.615	3.303	16.536
NPL	The ratio between non-performing loans and average of total loans and leases at quarter *t* and *t-1* (%).	73,210	3.105	2.095	3.069	0.000	13.903
Panel B. Independent Variables							
Post× Acquisition	A dummy variable that equals one for all quarters post-acquisition (for deals equals one for all quarters after the last acquisition in the deal)	73,210	0.104	0.000	0.306	0.000	1.000
RE Loans	Real estate loans divided by total loans	73,210	51.679	50.742	22.619	5.634	95.539
CI Loans	Commercial and industrial loans divided by total loans	73,210	22.110	19.795	12.808	1.066	59.544
Consumer Loans	Consumer loans divided by total loans	73,210	14.920	12.243	12.815	0.041	57.226
Size	The natural logarithm of total assets in real terms (2012 as the reference year) in thousands of US$.	73,210	12.274	12.090	1.346	9.717	16.392
Deposits	Total deposits divided by total assets (%)	73,210	87.408	89.173	6.384	64.092	95.458
Liquid Assets	Cash and balances due from depository institutions scaled by total assets (%)	73,210	7.547	6.050	5.516	1.068	28.122
Inefficiency	Non-interest expense/ (net interest margin + non-interest income)	73,210	0.728	0.691	0.237	0.322	1.621

Table 3: Long-Term Effects of Failed Bank Acquisitions

This table presents the fixed effects panel data regression model results for the evolution of the profitability, capital and NPL of the combined entity after failed bank acquisitions. The estimation window ranges from -5;+5 years around the event. In the first three columns, we present the models for the full sample period. In the last three columns, we focus on deals announced during the period 2008-2013. **ROE** is the ratio between net income and total equity**. Capital** is the ratio between equity and total assets. **NPL** is non-performing loans divided by total loans. The main explanatory variable is **Post × Acquisition** (a dummy variable that equals one for all quarters following an acquisition, and zero otherwise). The control variables include real estate loans divided by total loans (**RE Loans**); commercial and industrial loans scaled by total loans (**CI Loans**); consumer loans scaled by total loans (**Consumer Loans**); the natural logarithm of total assets in real terms in thousands of US$ (**Size**); the ratio between deposits and total assets (**Deposits**); cash and balances due from depository institutions scaled by total assets (**Liquid Assets**); non-interest expense/(net interest margin + non-interest income) (**Inefficiency**). All control variables are included in the model with a two-quarter lag. All models include state-by-quarter fixed effects (**State-by-Quarter FE**) and are estimated with robust standard errors clustered by bank (presented in parentheses). *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Full Sample			2008-2013	
	ROE	Capital	NPL	ROE	Capital	NPL
Post × Acquisition	2.011***	-0.121	-0.713***	2.113***	0.377	-0.420*
	(0.159)	(0.091)	(0.126)	(0.231)	(0.260)	(0.250)
RE Loans$_{t-2}$	0.025***	-0.014***	-0.013**	0.015	-0.017	-0.015
	(0.006)	(0.004)	(0.006)	(0.013)	(0.016)	(0.016)
CI Loans$_{t-2}$	-0.003	-0.011**	-0.011*	-0.017	-0.011	-0.049**
	(0.007)	(0.005)	(0.006)	(0.015)	(0.021)	(0.021)
Consumer Loans$_{t-2}$	0.028***	-0.011**	-0.030***	0.038*	-0.014	0.009
	(0.008)	(0.005)	(0.006)	(0.022)	(0.032)	(0.024)
Size$_{t-2}$	-0.990***	-1.453***	0.720***	-0.790***	-2.463***	0.592***
	(0.133)	(0.131)	(0.102)	(0.229)	(0.368)	(0.182)
Deposits$_{t-2}$	0.025***	-0.174***	0.030***	0.015	-0.170***	0.029***
	(0.007)	(0.013)	(0.006)	(0.009)	(0.022)	(0.009)
Liquid Assets$_{t-2}$	0.011	0.010*	-0.010	-0.014	-0.004	0.001
	(0.008)	(0.005)	(0.006)	(0.011)	(0.012)	(0.011)
Inefficiency$_{t-2}$	-3.962***	-0.828***	1.895***	-2.997***	-0.554***	1.599***
	(0.212)	(0.106)	(0.103)	(0.253)	(0.180)	(0.155)
Constant	12.361***	43.116***	-8.240***	11.334***	58.035***	-6.434**
	(1.792)	(1.893)	(1.535)	(3.218)	(4.953)	(2.694)
Observations	73,210	73,210	73,210	18,985	18,985	18,985
R-squared	0.324	0.747	0.605	0.477	0.689	0.681
Bank/State-by-Quarter FE	✓/✓	✓/✓	✓/✓	✓/✓	✓/✓	✓/✓

Table 4. Failed Bank Acquisition Effects on Profitability, Capital and Risk by Acquisition Relative Size

This table presents the fixed effects panel data regression model results for the profitability, capital and risk of the combined entity by acquisition size after failed bank acquisitions. The dependent variables include Return on Equity (**ROE**), the equity ratio (**Capital**), and Non-Performing Loans (**NPL**). The main explanatory variables are **Post × Small Relative Size** and **Post × Large Relative Size**, which are respectively dummy variables that equal one for all quarters following a small and large acquisition, and zero otherwise. Small (large) acquisitions are defined as the acquisitions, where the relative size of the target to the acquirer is smaller (larger) than the first (last) quartile of the sample distribution. The control variables include real estate loans divided by total loans (**RE Loans**); commercial and industrial loans scaled by total loans (**CI Loans**); consumer loans scaled by total loans (**Consumer Loans**); the natural logarithm of total assets in real terms in thousands of US$ (**Size**); the ratio between deposits and total assets (**Deposits**); cash and balances due from depository institutions scaled by total assets (**Liquid Assets**); non-interest expense/(net interest margin + non-interest income) (**Inefficiency**). All control variables are included in the model with a two-quarter lag. All models include state-by-quarter fixed effects (**State-by-Quarter FE**) and are estimated with robust standard errors clustered by bank (presented in parentheses). Panel B reports the equality tests of the Post × Small Relative Size and Post × Large Relative Size parameter estimates. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1) ROE	(2) Capital	(3) NPL
Panel A. Regression Results			
Post × Small Relative Size	0.287	-0.291**	0.152
	(0.268)	(0.136)	(0.180)
Post × Large Relative Size	3.601***	0.013	-1.324***
	(0.339)	(0.222)	(0.336)
Constant	12.538***	42.979***	-8.278***
	(1.790)	(1.899)	(1.535)
Observations	73,210	73,210	73,210
R-squared	0.323	0.747	0.604
Bank/State-by-Quarter FE/ Controls	✓/✓/✓	✓/✓/✓	✓/✓/✓
Panel B. Linear Equality Tests for Parameter Estimates			
Post× Small Relative Size =Post× Large Relative Size	**3.314*** (61.95)**	0.303 (1.40)	**1.475*** (15.64)**

Table 5. Failed Bank Acquisition Effects on Acquirers' Profitability and Risk –Efficiency Gap

This table presents the fixed effects panel data regression model results for the profitability, capital and risk of the combined entity by acquisition size after failed bank acquisitions. The dependent variables include Return on Equity (**ROE**), the equity ratio (**Capital**), and Non-Performing Loans (**NPL**). The main explanatory variables are **Post × Low Efficiency Gap** and **Post × High Efficiency** Gap which are respectively dummy variables that equal one for all quarters following a low and high efficient acquisitions, and zero otherwise. Low (High) efficient acquisitions are defined as the acquisitions, where the difference between the inefficiency of the acquirer and the target is larger (smaller) than the last (first) quartile of the sample distribution. The control variables include real estate loans divided by total loans (**RE Loans**); commercial and industrial loans scaled by total loans (**CI Loans**); consumer loans scaled by total loans (**Consumer Loans**); the natural logarithm of total assets in real terms in thousands of US$ (**Size**); the ratio between deposits and total assets (**Deposits**); cash and balances due from depository institutions scaled by total assets (**Liquid Assets**); non-interest expense/(net interest margin + non-interest income) (**Inefficiency**). All control variables are included in the model with a two-quarter lag. All models include state-by-quarter fixed effects (**State-by-Quarter FE**) and are estimated with robust standard errors clustered by bank (presented in parentheses). Panel B reports the equality tests of the Post × Low Efficiency Gap and Post × High Efficiency Gap parameter estimates. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1) ROE	(2) Cap	(3) NPL
Panel A. Regression Results			
Post × Low Efficiency Gap	1.446***	-0.355**	-0.381
	(0.343)	(0.177)	(0.260)
Post × High Efficiency Gap	2.444***	0.230	-1.017***
	(0.257)	(0.198)	(0.249)
Constant	13.691***	43.058***	-8.728***
	(1.808)	(1.891)	(1.546)
Observations	73,210	73,210	73,210
R-squared	0.322	0.748	0.604
Bank/State-by-Quarter FE/ Controls	✓/✓/✓	✓/✓/✓	✓/✓/✓
Panel B. Linear Equality Tests for Parameter Estimates			
Post × Low Efficiency = Post × Efficiency	**0.997** (5.84)**	**0.585** (4.68)**	**0.637* (3.31)**

Table 6. Failed Bank Acquisition Effects on Acquirers' Profitability and Risk – Business and Network Overlap Effects

This table presents the fixed effects panel data regression model results for the profitability, capital and risk of the combined entity by acquisition size after failed bank acquisitions. The dependent variables include Return on Equity (**ROE**), the equity ratio (**Capital**), and Non-Performing Loans (**NPL**). The main explanatory variables are **Post × Low Overlap** and **Post × High Overlap**, which are respectively dummy variables that equal one for all quarters following an acquisition with low and high business and network overlaps, and zero otherwise. Low (High) business overlap acquisitions are defined as the acquisitions, where the Jaccard loan portfolio similarity measure (Equation (3)) between the acquirer and the target(s) is smaller (larger) than the first (last) quartile of the sample distribution. Low (High) network overlap acquisitions are defined as the acquisitions, where the Branch Similarity measure (Equation (4)) between the acquirer and the target(s) is smaller (larger) than the first (last) quartile of the sample distribution. The control variables include real estate loans divided by total loans (**RE Loans**); commercial and industrial loans scaled by total loans (**CI Loans**); consumer loans scaled by total loans (**Consumer Loans**); the natural logarithm of total assets in real terms in thousands of US$ (Size); the ratio between deposits and total assets (**Deposits**); cash and balances due from depository institutions scaled by total assets (**Liquid Assets**); non-interest expense/(net interest margin + non-interest income) (**Inefficiency**). All control variables are included in the model with a two-quarter lag. All models include state-by-quarter fixed effects (**State-by-Quarter FE**) and are estimated with robust standard errors clustered by bank (presented in parentheses). Panel B reports the equality tests of the Post × Low Overlap and Post × High Overlap parameter estimates. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Business Overlap			Network Overlap	
	ROE	Cap	NPL	ROE	Cap	NPL
Panel A. Regression Results						
Post × Low Overlap	1.637***	-0.155	-0.670***	1.293***	0.001	-0.578**
	(0.297)	(0.153)	(0.248)	(0.271)	(0.194)	(0.241)
Post × High Overlap	1.912***	-0.052	-0.472**	2.038***	-0.324***	-0.867***
	(0.265)	(0.193)	(0.221)	(0.281)	(0.124)	(0.200)
Constant	13.556***	43.046***	-8.688***	13.411***	43.119***	-8.523***
	(1.822)	(1.898)	(1.548)	(1.819)	(1.896)	(1.542)
Observations	73,210	73,210	73,210	73,210	73,210	73,210
R-squared	0.321	0.747	0.603	0.321	0.747	0.604
Bank/State-by-Quarter FE/ Controls	✓/✓/✓	✓/✓/✓	✓/✓/✓	✓/✓/✓	✓/✓/✓	✓/✓/✓
Panel B. Linear Equality Tests for Parameter Estimates						
Post × Low Overlap= Post × High Overlap	-0.276	-0.103	-0.197	**-0.745***	0.324	0.289
	(0.50)	(0.18)	(0.37)	**(3.71)**	(1.90)	(0.86)

Table 7. Failed Bank Acquisition Effects on Acquirers' Profitability and Risk – Resolution Costs and SLA Effects

This table presents the fixed effects panel data regression model results for the evolution of ROE, Capital and NPL of the combined entity after failed bank acquisitions. The estimation window ranges from -5;+5 years around the event. In the first three columns, we present the models without controls. In the last three columns, we control for a set of bank characteristics. **ROE** is the ratio between net income and total equity**. Capital** is the ratio between equity and total assets. **NPL** is non-performing loans divided by total loans. The main explanatory variable is **Post × Acquisition** (a dummy variable that equals one for all quarters following an acquisition, and zero otherwise). The control variables include real estate loans divided by total loans (**RE Loans**); commercial and industrial loans scaled by total loans (**CI Loans**); consumer loans scaled by total loans (**Consumer Loans**); the natural logarithm of total assets in real terms in thousands of US$ (**Size**); the ratio between deposits and total assets (**Deposits**); cash and balances due from depository institutions scaled by total assets (**Liquid Assets**); non-interest expense/(net interest margin + non-interest income) (**Inefficiency**). All control variables are included in the model with a two-quarter lag. All models include state-by-quarter fixed effects (**State-by-Quarter FE**) and are estimated with robust standard errors clustered by bank (presented in parentheses). Panel B reports the equality tests of the Post × Low Resolution Cost and Post × High Resolution Cost parameter estimates. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Resolution Costs Effect			SLA effect	
	ROE	Cap	NPL	ROE	Cap	NPL
Panel A. Regression Results						
Post × Low Resolution Cost	1.235***	-0.201	-0.307			
	(0.307)	(0.123)	(0.245)			
Post × High Resolution Cost	1.988***	0.021	-0.551**			
	(0.311)	(0.220)	(0.260)			
Post × SLA deal				0.980*	0.241	0.651
				(0.541)	(0.427)	(0.543)
Constant	13.418***	43.043***	-8.715***	18.762**	72.464***	3.676
	(1.831)	(1.894)	(1.559)	(9.042)	(16.586)	(14.916)
Observations	73,210	73,210	73,210	2,393	2,393	2,393
R-squared	0.321	0.747	0.603	0.604	0.740	0.749
Bank/State-by-Quarter FE/ Controls	✓/✓/✓	✓/✓/✓	✓/✓/✓	✓/✓/✓	✓/✓/✓	✓/✓/✓
Panel B. Linear Equality Tests for Parameter Estimates						
Low versus High Costs	**0.753***	0.222	0.244	-	-	-
	(3.06)	(0.80)	(0.47)			

Table 8. Failed Bank Acquisition Effects on Profitability, Capital and Risk by Failure Intensity

This table presents the fixed effects panel data regression model results for the profitability, capital and risk effects of failed bank acquisition on the combined entity by failure intensity. The dependent variables include Return on Equity (**ROE**), the equity ratio (**Capital**), and Non-Performing Loans (**NPL**). The main explanatory variables are **Post×Low Failure Intensity** and **Post×High Failure Intensity**, which are respectively dummy variables that equal one for all quarters following an acquisition in a low and high failure intensity state, and zero otherwise. **Low Failure Intensity (High Failure Intensity)** acquisitions are defined as the acquisitions, that occur in the state and quarter where the ratio of failed banks over the total number of banks falls below (above) the last quartile of the sample distribution. The state is based on the state, where the acquirer is headquartered. The control variables include real estate loans divided by total loans (**RE Loans**); commercial and industrial loans scaled by total loans (**CI Loans**); consumer loans scaled by total loans (**Consumer Loans**); the natural logarithm of total assets in real terms in thousands of US$ (**Size**); the ratio between deposits and total assets (**Deposits**); cash and balances due from depository institutions scaled by total assets (**Liquid Assets**); non-interest expense/(net interest margin + non-interest income) (**Inefficiency**). All control variables are included in the model with a two-quarter lag. All models include state-by-quarter fixed effects (**State-by-Quarter FE**) and are estimated with robust standard errors clustered by bank (presented in parentheses). Panel B reports the equality tests of the Post × Low Failure Intensity and Post × High Failure Intensity parameter estimates. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1) ROE	(2) Capital	(3) NPL
Panel A. Regression Results			
Post × Low Failure Intensity	1.385***	-0.097	-0.558**
	(0.335)	(0.226)	(0.258)
Post × High Failure Intensity	1.923***	0.079	-0.587***
	(0.264)	(0.161)	(0.226)
Constant	13.534***	42.984***	-8.668***
	(1.820)	(1.893)	(1.548)
Observations	73,210	73,210	73,210
R-squared	0.321	0.747	0.603
Bank/State-by-Quarter FE/ Controls	✓/✓/✓	✓/✓/✓	✓/✓/✓
Panel B. Linear Equality Tests for Parameter Estimates			
Post× Low Failure Intensity =Post× High Failure Intensity	0.538	0.176	0.029
	(1.65)	(0.40)	(0.01)

Table 9. Failed Bank Acquisition Effects on Z-score

This table presents the fixed effects panel data regression model results for the Z-score effects of failed bank acquisition on the combined entity by failure intensity. Z-Score is estimated as the ratio between the sum of Return on Assets (ROA) and Capital and a 4-quarter standard deviation of ROA. In Column (1) we present the results as in our benchmark model, whereas in Column (2) the results are reported using a matching process with regular acquisitions. The main explanatory variable in Columns (1) and (2) is **Post × Acquisition** (a dummy variable that equals one for all quarters following an acquisition, and zero otherwise). The main explanatory variables in Column (3) are **Post×Low Failure Intensity** and **Post×High Failure Intensity**, which are respectively dummy variables that equal one for all quarters following an acquisition in a low and high failure intensity state, and zero otherwise. **Low Failure Intensity (High Failure Intensity)** acquisitions are defined as the acquisitions, that occur in the state and quarter where the ratio of failed banks over the total number of banks falls below (above) the last quartile of the sample distribution. The state is based on the state, where the acquirer is headquartered. The control variables include real estate loans divided by total loans (**RE Loans**); commercial and industrial loans scaled by total loans (**CI Loans**); consumer loans scaled by total loans (**Consumer Loans**); the natural logarithm of total assets in real terms in thousands of US$ (**Size**); the ratio between deposits and total assets (**Deposits**); cash and balances due from depository institutions scaled by total assets (**Liquid Assets**); non-interest expense/(net interest margin + non-interest income) (**Inefficiency**). All control variables are included in the model with a two-quarter lag. All models include state-by-quarter fixed effects (**State-by-Quarter FE**) and are estimated with robust standard errors clustered by bank (presented in parentheses). Panel B reports the equality tests of the Post × Low Failure Intensity and Post × High Failure Intensity parameter estimates. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)
	Benchmark Model	Matching with Regular Acquisitions	Failure Intensity Effect
	Z-score	Z-score	Z-score
Panel A. Regression Results			
Post × Acquisition	0.285***	0.350***	
	(0.045)	(0.112)	
Post × Low Failure Intensity			0.111
			(0.111)
Post × High Failure Intensity			0.354***
			(0.075)
Constant	6.620***	7.784***	6.620***
	(0.678)	(1.932)	(0.678)
Observations	71,896	6,043	71,896
R-squared	0.563	0.593	0.563
Bank/State-by-Quarter FE/ Controls	✓/✓/✓	✓/✓/✓	✓/✓/✓
Panel B. Linear Equality Tests for Parameter Estimates			
Post× Low Failure Intensity =Post× High Failure Intensity	-	-	0.243*
			(3.16)