ESSAYS ON BANK COMPETITION AND REGULATION

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Abstract:

The systemic importance of banks in the financial system and the economy has been long recognized by researchers and policymakers. Banks provide essential services to both depositors and borrowers, facilitating all kinds of economic activities. This dissertation investigates the mechanism of bank competition and discusses its implications on bank customers, systemic stability of the banking system, and related policies.

In the first chapter, I study the role played by bidders' information quality in determining the allocative efficiency in auctions for failed banks. Taking advantage of the bidding data on failed-bank auctions during the most recent financial crisis, I structurally estimate a first price auction model featuring conditionally independent private information to infer bidders' valuation distribution and noise distribution. Through counter-factual simulations, I find a marginal reduction in bidders' noise leads to a significant improvement in allocative efficiency, much larger than the improvement in auction revenue. The contrast highlights that the revenue-motivated incentive to improve information quality is vastly weaker than the valuation-motivated one. Moreover, I also find better information quality strongly complements other two prevalent policy tools in place, including increasing participation and using of Loss Share Agreements, which protects acquirers against future loss on acquired assets. Exploiting this complementarity promotes more efficient auction outcomes.

In the second chapter, I investigate the magnitude and economic mechanism of spillover effects of bank failures. Specifically, I identify how each bank failure is affected by its peer banks' failures. Identification is obtained by exploiting the partial overlapping branch networks of banks. I find peer failures lead to lower failure probability of failed banks on average. Moreover, there exists significant heterogeneity in the spillover effects across different acquirer types. In particular, I find failure probability of an affected bank drops if the acquirer of the failed bank is also a peer

of the affected bank. The results reveal that the industrial organization structure among affected banks largely determines the direction and magnitude of the spillover effect. The findings also have important implications for the current policy regarding the resolution of failed banks.

In the third chapter, I study how changes in bank competition as a result of bank M&As affect bank performances at the branch level, as well as the impact on local mortgage lending. I exploit the within-bank cross-branch variation in whether there is a merging counterpart branch nearby, as a variation in changes in local competition condition at the branch level. I find that M&As lead to higher deposit growth for all involved branches on average. However, branches with merging counterpart branches nearby see a drop in deposits growth. Regions affected by M&As on average experience increase in mortgage loan denial rates, with an especially large increase in the regions with counterpart branches located closely. The results highlight the geographical heterogeneity in the consequences of bank consolidation.

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For my dearest family

Contents

Chapter 1

The Efficiency Effects of Information Quality in Failed-Bank Auctions

1.1 Introduction

When banks become extremely undercapitalized and likely to fail, the Federal Deposit Insurance Corporation (FDIC) has the discretion to take the banks into receivership before determining the best possible resolution method. In the resolution process, the FDIC's objective is to minimize the cost to its insurance fund, which is funded by taxpayers. Empirically, this objective typically leads the FDIC to use an auction mechanism to sell a failed bank as a whole to acquirers, rather than liquidate the assets piece by piece. Because bank capital is procyclical and bank failures cluster in economic downturns, asset transfers through these auctions not only affect the well-being of the targets and acquirers involved but may also have far-reaching effects on economic recovery by facilitating a smooth restructuring of the banking sector. In the decade following the most recent financial crisis, over 400 failed banks with around \$650 billion in book assets and \$400 billion in deposits were transferred through these auctions[1]. Meanwhile, about 500 banks, comprising about 10% of all US banks, bid in the auctions, and half of those bidding banks successfully acquired a bank in the auctions.

Ideally, failed banks should always be sold to bidders who value them the most, since such matching between bidders and targets creates the most economic value. The auctions generate such efficient outcomes when bidders have perfect signals about their valuation for targets because the bidder with the highest valuation always has the highest signal and thus bid. However, bidders' information quality is particularly concerning in failed bank auctions because the need for rapid resolution of all failed banks gives both the FDIC and bidders minimal time to gather and process information about the targets[2]. Poor information quality creates misalignment between bidders' signals and their valuation, leading to misallocation in which the winner does not have the highest true valuation. Hence, information quality is paramount for efficient outcome s in failed-bank auctions, especially given their large scale and profound systemic consequences.

I characterize the effects on auction efficiency of bidder's information quality, and how it interacts with other policy levers, by estimating a structural auction model proposed in Hong and Shum (2002). The Estimation uses bidding data for failed banks in the aftermath of the most recent financial crisis between 2009 and 2017. The model captures three crucial features of these auctions: the heterogeneity in the intrinsic quality of failed banks' assets, bidder-specific synergies with targets, and the noise in bidders' signals about the overall value of the targets. Signal noise drives the discrepancy between signals and true valuation in this framework, which allows for studying the effect of information quality on the efficiency of these auctions. Bidders

[1]The statistics are calculated using all Purchase and Assumption (P&A) transactions without the FDIC's financial assistance between 2007 and 2017.

[2]Granja et al. (2017) documents the typical due-diligence period for one bidder in failed-bank auctions is 4-6 days, compared to 3-4 months in regular M&A transactions according to Marquardt and Zur (2015)

take into account both competition from others and potential "winner's curse" when submitting their bids. The model is estimated using Simulated Method of Moments (SMM) that tries to match model-implied bid moments and empirical bid moments.

I find that the benefit of information quality improvement to value creation is substantial because misallocation is reduced: a marginal 1% decrease in the standard deviation of noise can lead to an increase in the expected winner's valuation, a measure of value creation, of up to 1.5%. The percentage translates to $1.2 billion over all failed-bank transactions in the sample. However, the effect of improved information quality on the expected winner's bid, a measure of auction revenue, is small relative to that on the winner's valuation, or even negative. Also, the expected winner's valuation is up to 4% higher if noise is eliminated, corresponding to $4.8 billion for the failed banks in the sample. As a comparison, the expected winner's bid only increases up to around 2% after elimination of noise in bidders' signals. The fact the benefit of improved information quality to auction revenue is much lower than that to value creation suggests that the revenue motivation to improve information quality is vastly weaker than the value creation motivation. It is worth noting that value creation is arguably more important in this context from a welfare standpoint because the auction revenue is merely a transfer between the FDIC and acquirers. However, the FDIC is likely more motivated by auction revenue considerations, given its Least Cost Resolution policy, which mandates that the agency chooses the resolution alternative with the lowest monetary cost. The framework is well suited to empirical study of the FDIC's revenue-maximizing incentive to improve information quality, because the effect of information quality on auction revenue is theoretically ambiguous when bidders have both synergy and winner's curse considerations.

The FDIC has policies in place concerning aspects of failed-bank auctions other than information quality, with the purpose of achieving more efficient auctions or reducing resolution cost. Therefore, studying how information quality works in conjunction with other policy levers is key to drawing relevant policy implications. Specifically, I investigate how information quality interacts with two other aspects: level of participation and the presence of flexible Loss Share Agreements (LSAs)[3], in affecting the value creation in these auctions. Encouraging more bidders to participate in the auctions, which is the purpose of the FDIC's effort to market failed banks, may raise auction revenue via intensified competition. An LSA, a special feature in failed-bank auctions provided by the FDIC, is partial insurance for bidders in which the FDIC shares a fraction of the loss on the acquired assets. Flexible LSAs allow bidders to choose the loss share fraction, which affects the valuation distribution among bidders pooling in the same auction and further affects the efficiency of the auction outcomes.

I find information quality greatly complements the value effect of participation: the increase in value creation from one additional bidder in an auction is over two times higher if the noise in bidder's signals is eliminated. The result occurs because the additional bidders raise not only the expected winner's valuation, but also the probability of misallocation, leaving the net effect of additional bidders theoretically unclear. Better information quality can, therefore, counteract the increased misallocation cost from more participation. I also find information quality strongly complements flexible LSAs: the increase in expected winner's valuation from flexible LSAs is over 60% higher if noise is eliminated. This result comes from the fact that the bidders' valuation distribution under flexible LSAs generates significantly higher expected winner's valuation but is also more prone to noise-induced misallocation. Hence, better information quality can help realize a much larger benefit of LSA flexibility for value creation.

My findings have implementable policy implications. Most importantly, the contrast between the value and revenue effects of information quality improvement reveals

[3]They are also referred to as Shared-Loss Agreements (SLAs) sometimes.

a potential tension between value-maximizing and revenue-maximizing choices of information quality. The Least Cost Resolution policy, motivating the FDIC to focus on monetary cost in its resolution practices, could drive such tension and lead to sub-optimal policy choices from a value creation perspective. While there are convincing reasons for requiring the FDIC to focus on monetary costs, such as anti-corruption considerations, it is helpful to examine potential relaxation of these requirements in some cases to achieve more efficient auction outcomes. In addition, information quality strongly complements other policy levers such as promoting participation and flexible LSAs, suggesting that combining them and exploiting their complementarity can more effectively enhance value creation in auctions. Practically, the FDIC could extend the due diligence period for bidders when a target bank has a particularly complex book, or when the number of participating bidders is large, subject to the cost of delaying the resolutions.

Methodologically, my paper overcomes many technical and empirical challenges to reach these inferences. This paper is the first study that adopts a structural first-price auction model to investigate failed-bank auctions. This framework is essential because different aspects of an auction including information quality, participation, and LSA usage, have a theoretically ambiguous impact on bidding behavior. In addition, I also utilize the Expectation Maximization (EM) algorithm to deal with missing value problems that are due to the way the FDIC discloses bid information. The algorithm helps illuminate how bidders with different characteristics value failed banks differently. Further, I also take advantage of a novel network embedding approach stemming from the deep learning literature. This approach can generate position representations of all banks within the entire banking system and form important control variables largely not captured by financial data.

1.1.1 Related Literature

This paper is most closely related to Granja (2013), which investigates the relationship between the disclosure requirements on failed banks and their resolution outcomes. This is also the first paper looking at the bidding data in the most recent financial crisis. The author finds that the FDIC incurs lower resolution cost and retains less assets when resolving failed banks under more comprehensive disclosure requirements before their failures. My structural framework adds to the work above by separating the effects of information quality on allocative efficiency and auction revenue, extending our understanding of the role played by information environment in the failed bank resolutions.

This paper is also related to other empirical studies of failed-bank auctions. Gilberto and Varaiya (1989) pioneers that literature, finding that the observed bid distribution has features of both private value and common value auctions. Zhang (1997) also studies failed-bank transactions, with a focus on repeat acquirers. He finds that repeat acquirers earn significant positive abnormal returns, while first-time acquirers on average do not profit from their transactions. Cowan and Salotti (2015) studies the announcement effects on stock prices of the acquirers acquiring failed banks in the most recent crisis and find these acquirers have significant wealth gain from the transactions. Granja et al. (2017) show evidence for misallocation of failed banks' assets due to capital constraints. Lambert et al. (2017) finds the lobbying effort of the bidders in failed-bank auctions can increase their chance of winning the auctions. They further show that these auction outcomes may be suboptimal in that the FDIC incurs more resolution cost. Vij (2018) studies the real consequences of acquiring failed banks and finds that acquirers tend to cut lending to failed banks' borrowers, and lower deposit rates for all depositors.

Two prior studies use structural approaches to investigate failed-bank resolutions. Kang et al. (2015) estimates a dynamic discrete choice model of the FDIC's choice of whether and when to close a bank to quantify the direct and indirect cost of closing a bank. The research points out that the FDIC faces significant nonmonetary considerations in deciding when to close a bank. Akkus et al. (2016) takes a closer look at the auctions and bids in the failed-bank transactions and estimates a matching model between the targets and bidders, which provides evidence of how different bidders value targets with different characteristics. The main idea of their approach is based on revealed preference: the observed matching between targets and acquirers in the failed-bank transactions must have a higher value for the acquirers than other possible matchings. They find that the valuation increases with target-acquirer market overlap, suggesting a market power motive for mergers.

Methodologically, this paper adopts a structural first-price sealed auction featuring symmetric conditionally independent private information (CIPI) studied in Li et al. (2000), Hong and Shum (2002), and Li et al. (2002). I parametrically estimate the model using simulated methods of moments (SMM), as seen in Levin et al. (2011) and Dimopoulos and Sacchetto (2014).

The rest of the paper is organized as follows. Section 1.2 introduces the institutional background of failed-bank auctions. Section 1.3 describes the data sources and the sample used in this paper. Section 1.4 documents some model-free regression results on the roles played by information quality and LSAs in the studied auctions. Section 1.5 explains the structural auction model and its estimation. Section 1.6 presents the results from counterfactual analyses based on the structural estimates. Section 3.4 concludes with the main findings and their policy implications.

1.2 Failed-Bank Auctions

1.2.1 Auction Process

A typical failed-bank resolution starts with a bank's primary regulator notifying the FDIC of the potential failure, usually the result of critical undercapitalization or insolvency. The FDIC then visits the failing institution and gathers information about its financial and operational conditions, in preparation for a resolution process, if it is needed. The failing institution is then marketed to potential buyers, without any identifiable information. All potential buyers who decide to participate in the bidding then have to sign confidentiality agreements, so they do not disclose any information about the bank during the resolution process. The FDIC then gives all bidders access to a virtual data room containing all financial and operational information collected by the agency. Upon reviewing this information, bidders may apply for on-site due diligence. If approved by the FDIC, the bidder may send its specialists to the failed institution to collect additional information. The bid submission window that opens after this information gathering and processing phase typically lasts around a week, during which new information can still be added for bidders to access. After the deadline for bid submission, the FDIC conducts its least-cost analysis and pick the bidder that leads to the lowest resolution cost as the winner. This process typically only lasts several days. Once the winner is chosen, the failed bank is usually closed after Friday business hours. All transactions of the failed bank then take place over the weekend, and it reopens on the next business day under the name of the acquirer.

1.2.2 Loss Share Agreement

A loss share agreement (LSA), a special feature in failed-bank acquisitions not seen in other M&A transactions, is similar to a put option that acquirers can exercise if the assets acquired end up having charge-offs or liquidation losses.[4]. Typically, LSAs cover both residential and commercial mortgage loans, which are divided into three tranches respectively according to the riskiness of these assets. An LSA specifies the fraction of assets covered by the agreement in each tranche and comes into effect when the acquirer sells the covered assets upon the FDIC's approval at a loss or writes off the covered assets due to borrower default. The standard loss share rule is that the FDIC will absorb 80% of the loss in the first and third tranches while the acquirer only bears 20%. The FDIC usually specifies the loss share percentage of the second tranche, which is intended to provide sufficient incentive for the acquirers to manage the acquired assets properly so that the loss will not cross into the second tranche. In addition, the FDIC keeps monitoring the management of the assets covered by the agreement continuously after the transaction to make sure the acquirer exerts the effort necessary to mitigate potential losses. Acquirers with assets covered by LSAs are usually only allowed to sell these assets after a certain period and with the FDIC's approval.

When the FDIC evaluates the resolution cost associated with all bids in an auction, it calculates the expected cost of providing an LSA, if one exists in a bid, using its proprietary model, and includes it as part of the resolution cost.

The introduction of LSAs in failed-bank acquisitions can be dated back to the early 1990s [5], but the recent financial crisis saw the first large scale use of such agreements. In the decade following the recent crisis, the FDIC provided LSAs to about 300 failed-bank transactions, covering around $200 billion in assets. The purpose of the LSAs is to encourage whole bank transactions and reduce the FDIC's receivership cost. Prior to the wide adoption of LSAs, the FDIC usually had to retain a considerable amount

[4]LSAs differ from a typical put option in at least the following two ways. First, the downside risk of the acquired assets is not completely capped because the acquirer always has to bear a fraction of the loss. Second, the FDIC is entitled to share a fraction of the profit, if the assets are sold at a premium.

[5]See FDIC (1997) for details at https://www.fdic.gov/bank/historical/managing/

of a failed bank's assets, with the acquirer assuming only safer assets. The retained assets impose a significant administrative burden on the FDIC, which has to liquidate the assets over a prolonged period. LSAs encourage bidders to take a failed bank "as is," and the bidders are willing to do so since the FDIC is providing downside protection through the LSAs. Most failed-bank transactions occurring during the financial crisis have LSAs.

Starting April 2010, the FDIC modified LSA implementation to allow more flexible terms (Archer, 2012) [6]. Specifically, allowing bidders for targets with over $500 million in assets to specify a loss share percentage different from the default 80/20 sharing rule. Intuitively, bidders can bid more "aggressively" by specifying a lower loss share percentage. The first cases took place in mid-April 2010, when TD Bank acquired three failed banks with 50% loss share. In Appendix 1.H, I plot the loss share percentage over all observed bids in the sample around Q2, 2010. It is easy to see that bidders chose many nonstandard loss share percentages after Q2, 2010.

1.3 Data

1.3.1 Source

The FDIC started disclosing detailed auction information in late 2009. Bid information is available on the FDIC website for auctions occurring after May 2009. Briefly speaking, the information includes the following: the top two bids and the identities of the top two bidders[7], all other losing bids with undisclosed bidder identities, and the identities of all losing bidders.

[6] See https://mercercapital.com/article/changes-to-loss-share-agreement-terms-should-be-considered/ for a brief report.

[7] The identity of the cover (second place) bidder is usually only available one year after the transaction.

Bids typically include at least two core components: asset premium (discount) and deposit premium (discount), where the former is usually a dollar amount, and the latter is a percentage. To demonstrate how these two numbers determine the final transaction price, consider an auction for a failed bank with \$100 million in book assets, and \$110 million in book deposits. The bank does not have any other liabilities. Now consider a bid that has an asset premium of $-\$10$ million, and a deposit premium of 10%. Intuitively, one can think of the bid as saying the asset is only worth $\$100 - \$10 = \$90$ million to the bidder, whereas the deposit liability is worth $\$110 \times (1 + 10\%) = \$121$ million. The final transaction price will be the net worth or equity value implied by the bid. In this example, the net worth implied by the bid is $\$90 - \$121 = -\$31$ million. In this case, the bidder is essentially saying it is willing to take over the failed bank if the FDIC pays it \$31million, which constitutes part of the agency's resolution cost. The bidder pays the FDIC the bid amount if the net equity value implied by the bid is positive.

In practice, bidders often have the flexibility to specify many other aspects of the transactions. Notable examples of additional terms in a bid include the following:

- **Loss Share Agreement.** Bidders can choose if they want an LSA with a transaction. For targets with over \$500 million in book assets after April 2010, they can further specify how much loss share they want. The FDIC calculates the cost of providing the LSA using its proprietary model and includes it as part of the resolution cost on top of the bid amount.

- **Insured Deposits.** Bidders can choose to assume only insured deposits, instead of all deposits, as in most of the transactions.

- **Value Appreciation Instrument.** This is a warrant that public bidders can offer to the FDIC so that the FDIC can share part of the gains from the transactions. This is relatively rare in all the observed auctions.

The disclosed bid information gives fairly good details of all the terms above. Moreover, bidders are allowed to submit multiple bids with different transaction types. For example, a bidder can submit one bid with an LSA and one without. The flexibility creates the complication that bidders can effectively bid on different objects in the auction for the same failed bank since bids with different transaction terms are not directly comparable. To prepare the raw bid data so that they can be analyzed under a first price auction framework, I introduce the notion of a "pool" for all auctions where multiple transaction terms are involved. Two bids belong to the same pool if and only if their transaction terms are exactly the same, i.e., the same loss share amount, the same set of deposits, and so on.

1.3.2 Sample Construction

There are 453 bank failures in the sample period between July 2, 2009 and October 13, 2017, of which 433 are purchase and assumption transactions (P&A) and the remaining 20 are direct payoffs without any acquirer. I then obtain the bid summaries of these purchase and assumption transactions from the FDIC website. The bid summaries are usually tables containing all important details of the bids, including all aspects discussed in the last section. I assign bids to pools according to all available bid terms. In other words, two bids in the same pool have exactly the same observable bid terms in all columns of the bid summary table. I only keep bids when there are at least two bids in the same pool, thus losing a significant fraction of the entire sample of failed-bank auctions because many auctions early in the financial crisis have only one bidder. One failed-bank auction could have multiple pools with at least two bids. I keep all these pools to maximize the sample size for further analysis. If any bid in the auction is "linked," I drop the entire auction from the sample[8]. In some cases,

[8]For these auctions, bidders are bidding on multiple objects simultaneously, and the objects may have different complementarity and substitutability. Hence, the bidders optimal bidding strategy

one bidder submits multiple bids of slightly different amounts. I keep only a bidder's highest bid whenever it is possible to identify the bidder.

The final bid sample consists of 882 bids in 304 pools for 213 failed banks. Among all the bids, 872 are for whole bank transactions, 535 include LSAs, and 867 are for all deposits.

The bids are defined as follows

$$bid = \frac{asset\,premium + book\,deposits \times deposit\,premium}{book\,assets}$$

Intuitively, the bids are the premium/discount of a failed bank expressed as a percentage of its book assets. Book deposits is the book value of all deposits or insured deposits, depending on which parts of deposits are included in a bid. The vast majority of bids are negative, meaning the FDIC has to pay the bidders.

The bid sample is the core sample used in the structural estimation. I construct the financial and geographical characteristics of the target banks using the Call Reports and Summary of Deposits, which are then matched to this bid sample.

In addition, I construct a sample of the characteristics of all bidders participating in the auctions in the bid sample. This sample is used to analyze how bidder characteristics affect their valuation.

It is worth noting that the geographic location is critical for the depository institutions studied here since the geographic coverage of the branch network of a bank largely determines its customer base and competitors. Each bank is to an extent unique because of its unique geographic location within the national banking system. Therefore, it is essential to have variables to capture this geographic uniqueness. Intuitively, the branch network of one bank can be represented by a vector of length M, where M is the total number of markets. Each entry of the vector indicates

can be vastly different from that in a single object first price auction, which is the base of the framework I will use to analyze the data.

whether or not the bank is in that market. Similarly, the set of competitors of one bank can be represented by a vector of length N, where N is the total number of banks. Each entry in this vector then indicates whether the bank is competing with the other bank in at least one market[9]. However, this type of representation is not feasible for the analysis due to its high dimensionality[10]. For example, to understand how much variation in bids can be explained by the identity of a target's competitors, I could regress bids on the target's competitor representation. However, this regression is infeasible because I only have about 900 observations, while there are over 9000 regressors.

To address this problem, I utilize some dimension reduction techniques. For the market representation, I use Principal Component Analysis to compress all market representations into 16-dimension vectors. Intuitively, the process can be thought of as first clustering all locations of all bank's branches into 16 principal regions, so that the market representation of one bank is a 16-dimension vector representing the "exposure" of its branches to the 16 principal regions.

To compress the representations of competitive relationships, I utilize a state-of-the-art technique widely used in social network research, graph embedding[11]. The input is an undirected graph describing banks' competitive relationships in which each node represents a bank, and edges connecting two nodes mean the two banks are competitors because they both have branches in some counties. The task here is to find a low-dimension vector representation of each bank in this network, so the downstream analyses are feasible. I use the graph embedding algorithm pioneered by Perozzi et al. (2014). The basic idea of this algorithm is to find a vector representation

[9] I define markets as counties and competitors as another bank that operates in at least one same county as the bank. One alternative definition of a market is a Metropolitan Statistical Area (MSA). However, there are unnegligible number of banks only operate or mostly operate in non MSA areas. To retain as many observations as possible, I use county as the market definition.

[10] Given a market is a county, the market representations are vectors of length 3000, and the competitive relationship representations are vectors of length around 6000.

[11] An example task for graph embedding is to find a low-dimension vector representation of people within a social network, which could then be used for downstream tasks like friend recommendation.

of each node so that nodes connected have similar representation while nodes not connected have very different representations[12]. The output of this exercise is 16-dimension vectors for all banks that capture their competitive position within the entire national banking system. The details of the algorithm are available in Appendix 1.B.

It is worth emphasizing that the market representations and competitive relationship representations of the banks capture two drastically different aspects of banks' operating environment, even though the competitive relationship representations are constructed through the bank's market presence. The market representations describe the geographical coverage of banks' branch networks, whereas the competitive relationship representations only depict the competitors of banks, regardless of where these competitors are. This is because the competitive relationship representations are learned solely from the topology of the bank network, where there is no actual geographical location information. Another way to think about the difference between the two representations is that the geographical location of a bank determines many aspects of the bank's operation, and one such aspect is its competitors, which is captured by the competitive relationship representation. These representations are empirically important. In untabulated results, these representations alone can explain over 10% of the variation in observed bids, which is on a par with all the financial variables constructed from Call Reports data.

1.3.3 Descriptive Statistics

Table 1.1 presents the descriptive statistics of the sample. Panel A reports the summary statistics of three different groups of banks: failed banks, bidders who

[12]I use the node2vec algorithm proposed by Grover and Leskovec (2016). The representation learning task is framed as a maximum likelihood estimation problem, which looks for vector representations of all nodes, such that the likelihood of the observed bank network is maximized. I choose 16 as the dimension of the embedding, and the input network is the bank network of 2009. The number of dimension does not affect the analysis results too much. I choose 16 mostly for computational reasons. The representations can be learned in about 3 hours on a 12 core PC.

have participated in the auctions in my sample, and winners who have successfully acquired at least one failed bank through the auctions. It is intuitive to see the failed banks are very poorly capitalized before the auctions since they have very low equity ratio compared with the other two groups. These failed banks also have very high nonperforming loan ratio. It is also worth noting that the failed banks are one to two orders of magnitude smaller than the bidders and winners. This is partly due to the sample construction process. For many large failed banks, the auction setup differs from that for these smaller failed banks. Hence, these larger failed-bank auctions are not in the sample due to their low comparability with other auctions. Panel B reports the summary statistics of the bids, which are mostly negative, meaning the FDIC will actually pay the bidders to assume the failed-banks.

1.4 Model-Free Results

This section documents some model-free results on how information quality and LSAs affect the observed bids, which may provide some hint as to their roles in the auction process.

1.4.1 Bids and Receivership Duration

Both researchers and practitioners consider premerger due diligence in M&A transactions to be critical to reduce the information asymmetry between the target and the bidder, thus increasing the likelihood of a successful transaction ((Marquardt and Zur, 2015; Wangerin, 2017; Perry and Herd, 2004; Howson, 2003)). In failed-bank transactions, the need for rapid resolution creates concerns for the quality of due diligence, as bidders have very limited time to process the FDIC-provided information, and to conduct additional assessment via on-site visits.

Panel A: Bank Characteristics

Type	Count	Equity Ratio	Loan Ratio	OREO Ratio	NPL Ratio	Size	Age	#Branches	#Auctions
Failed	213	0.010	0.678	0.058	0.015	0.405	41.6	5.3	
		(0.024)	(0.102)	(0.051)	(0.034)	(0.779)	(39.7)	(6.8)	
Bidder	271	0.120	0.653	0.011	0.002	5.816	59.7	59.5	2.59
		(0.043)	(0.126)	(0.012)	(0.005)	(26.700)	(44.3)	(207.7)	(4.29)
Winner	134	0.123	0.645	0.012	0.002	11.531	57.2	85.9	4.25
		(0.054)	(0.132)	(0.014)	(0.003)	(45.651)	(44.9)	(286.2)	(5.92)

Panel B: Bid Statistics

	Mean	Std	5%	25%	Median	75%	95%
Deposit Premium (%)	0.23	0.54	0	0	0	0.15	1.05
Asset Premium (%)	-15.44	10.45	-35.05	-20.10	-13.12	-9.04	-2.59
Bid (%)	-15.78	10.22	-35.25	-20.37	-13.38	-9.33	-2.78

Panel C: Auction Pool Statistics

#Bidders	2	3	4	5	6	Total
Count	148	78	50	16	12	304

Table 1.1: **Descriptive Statistics:** This table reports a variety of summary statistics of the data used in this paper. Panel A reports the financial conditions of three groups of banks. “Failed” are the targets of the auctions in my sample. “Bidder” are the banks that have participated in any auction in the sample. “Winner” are the banks that successfully acquired at least one failed bank through the auctions in the sample. #Branch is the number of physical branches of the bank. #Auction is the number of auctions the bank participated in the whole sample. More variable definitions are in Appendix 1.G. The reported numbers are the averages of the variables above, computed using the data of the last Call Reports before the corresponding transactions. Standard deviations of these variables are in the parentheses. Panel B reports the summary statistics of the bids. Deposit Premium (%) is obtained from the deposit premium column in bid summary tables. Asset Premium (%) is the asset premium in dollar amount reported in bid summary tables scaled by the book assets of the target. Bid (%) is the premium of the bid over the book equity scaled by the book assets. All the numbers are in percentage points. Panel C reports the number of bidders in the auction pools constructed from the raw bid summary data.

In recent accounting literature ((Marquardt and Zur, 2015; Amel-Zadeh and Zhang, 2015; Wangerin, 2017)), researchers use the number of days between the signing of a confidentiality agreement and deal completion as the proxy for the effort in or quality of due diligence because the exact length of due diligence is unobservable. Following the same idea, I use the time elapsed between the date a target's capital ratio drops below 2% and the date the institution closes as my proxy for the duration of the receivership[13]. This count should capture the time available for information gathering and due diligence, permitting the development of insights into how the amount of time available affects bidding behaviors.

Table 1.2 reports the results of regressing observed bids on the receivership duration and four exhaustive sets of control variables, including target financial characteristics, loss share terms, target markets, and target competitive environment. The main variable of interest is $Months$, which is the proxy for receivership duration in months. I only report the coefficient before $Months$ for expositional tidiness. All columns except Column (1) show that there is a strong positive association between the average bids in an auction and its receivership duration. That is, all else equal, auctions with longer resolution process receive higher bids from the bidders. The results are consistent with the interpretation that bidders bid more aggressively when the time constraint is more relaxed in a longer resolution process. Whether or not the association is causal, this finding is suggestive evidence that information quality is crucial for bidders' behaviors, and ultimately for auction outcomes.

1.4.2 Bids and Loss Share Agreements

As a special instrument in failed-bank auctions, LSAs are also critical to bidding strategy. Table 1.3 reports the relationship between LSA terms and bids, conditional

[13]The capital ratio is computed from the quarterly Call Reports. The length is the number of days between the filing date of the corresponding Call Reports and the closing date.

Dependent Variable: Bid				
Variables	(1)	(2)	(3)	(4)
Receivership Duration	0.000	0.006***	0.005***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Target Financials	Yes	Yes	Yes	Yes
Loss Share	No	Yes	Yes	Yes
Target Market	No	No	Yes	Yes
Target Embedding	No	No	No	Yes
Observations	882	882	882	882
$Adj.R^2$	0.115	0.318	0.318	0.336

Table 1.2: **Bids and Receivership Duration**: This table reports regression results of variations of $bid_{it} = \beta_0 + \beta_1 ReceivershipDuration_t + X_t'\beta_2 + e_{it}$. Coefficients of $ReceivershipDuration_t$ are reported. $ReceivershipDuration_t$ is the number of months between the filing date of the earliest Call Reports before failure, in which the equity ratio of the target dropped below 0.02, and the closing date of the institution. X_t is a vector of control variables specific to each failed bank. *Target Financials* are eight variables constructed from each failed bank's last available Call Reports including equity-to-asset ratio, loan-to-asset ratio, OREO ratio, nonperforming loan ratio, ROA, liquidity ratio, total assets, and age. *Loss Share* includes six variables describing the loss share percentage of each tranche of assets covered by the LSA. *Target Market* is a 16-dimensional vector of loadings on first 16 principal components of the matrix whose ij-th element is a dummy variable equal to 1 if bank i was in county j in 2009. *Target Embedding* is a 16-dimensional vector representing the location of a bank in the graph depicting the competitive relationship among all banks in 2009, which captures the set of competitors faced by each bank. Standard errors are reported in parentheses, which are clustered at the failed bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

on different sets of control variables. All the target characteristics in Table 1.2 are included as controls, but I only report the loss share variables for simplicity.

In Column (1), the independent variable is a dummy equal to 1 if an auction includes an LSA and 0 otherwise. As expected, bids in auctions with LSAs are significantly higher than in the ones without. In particular, auctions with LSAs see 9 percentage points higher bids on average. Column (2) and (3) show the effects of some other variables capturing the terms of LSAs. As described before, the assets covered by LSAs are usually divided into six tranches: three tranches for single-family residential mortgages and three tranches for commercial mortgages. An agreement

Dependent Variable: Bid			
Variables	(1)	(2)	(3)
Loss Share	0.0922***		
	(0.011)		
All Tranches		0.1730***	
		(0.022)	
Single Family Tranches			0.0357**
			(0.018)
Commercial Tranches			0.1381***
			(0.022)
Observations	882	882	882
Adj. R^2	0.282	0.271	0.278
Target Controls	Yes	Yes	Yes

Table 1.3: **Bids and Loss Share Agreements**: this table reports the regression results of variations of $bid_{it} = \beta_0 + \beta_1 Loss\,Share\,Terms + X_t'\beta_2 + e_{it}$. *Loss Share* is a dummy variable equal to 1 if an LSA is included in the bid. *All Tranches* is the average loss share percentage across all six tranches of assets. *Single Family Tranches* is the average loss share percentage across three tranches of single-family mortgage loans. *Commercial Tranches* is the average loss share percentage across three tranches of commercial mortgage loans. *Target Controls* include target financial characteristics, markets, and embeddings as in Table 1.2. Standard errors are reported in parentheses, which are clustered at the failed bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

specifies the share fraction in each tranche. For example, the default share fraction in single-family tranche 1 is 80/20; that is, the FDIC will absorb 80% of the loss, and the acquirer will absorb the remaining 20%. The independent variable in Column (2) is the average share fraction across all six tranches. The results show that the higher the share fraction is, the higher the bidders are willing to bid. For each 1 percentage point increase in the share fraction, bids are expected to be higher by 173 basis points relative to the target's total assets. In fact, this relationship can be interpreted as a lower bound of the expected percentage loss from the assets acquired through failed-bank transactions. The expected loss has to be at least 17.3% of the value of the covered assets to justify the higher willingness to pay of the bidders. Column (3) shows the effects of loss share on residential mortgages and commercial mortgages separately. The results suggest that the loss share fraction on the commercial mortgages has a more substantial quantitative effect on bids.

1.4.3 Loss Share, Value Uncertainty, and Receivership Duration

The LSA is a common instrument allowing bidders to partially insure the potential loss from acquired assets. Intuitively, when bidders have high uncertainty regarding the value from acquiring a failed bank's assets, they would utilize the LSA more to insure against the uncertainty. I argue that the target-bidder relation is an important determinant of a bidder's uncertainty about a target's value. Hence, in this section, I look at how target-bidder relations correlate with bidders' utilization of LSAs, which can reveal the role of LSAs in bidding behavior. Specifically, I regress a loss share dummy on several variables that capture some aspects of the target-bidder relations. Columns (1) to (4) of Table 1.4 report the results.

The table contains three independent variables: $Distance$, $Market\,Similarity$, and $Embedding\,Similarity$. $Distance$ captures the physical distance between a bid-

	Dependent Variable: Loss Share Dummy						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance	0.8193**			0.3710	0.5716		
	(0.363)			(0.423)	(0.764)		
Market Sim.		-0.2089**		-0.2363*		-0.4562***	
		(0.100)		(0.120)		(0.167)	
Embedding Sim.			0.0323	0.2156			-0.0847
			(0.157)	(0.200)			(0.283)
Duration					-0.0634***	-0.1176***	-0.0527
					(0.019)	(0.025)	(0.045)
$Duration \times X$					-0.0612	0.0998***	-0.0055
					(0.229)	(0.038)	(0.068)
Target Controls	No	No	No	No	Yes	Yes	Yes
Observations	233	213	294	207	233	213	294
$Adj.\ R^2$	0.008	0.019	-0.003	0.021	0.221	0.308	0.165

Table 1.4: **Loss Share and Value Uncertainty**: column (1) to (4) of this table presents regression results of $LossShare_{it} = \beta_0 + X'_{it}\beta_1 + e_{it}$, where $LossShare_{it}$ is a dummy variable equal to 1 if an LSA is included in the bid., and X_{it} is a vector of variables capturing the value uncertainty of bidder i for target t. Column (5) to (7) presents the regression results of $LossShare_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Duration_t + \beta_3 Duration_t \times X_{it} + Z_t\eta + e_{it}$, where $LossShare_{it}$ and X_{it} are defined the same as above. *Duration* is the number of months between the filing date of the earliest Call Reports before failure, in which the equity ratio of the target dropped below 0.02, and the closing date of the institution. Z_t is a vector of target control variables including *Target Financials*, *Target Market*, and *Target Embedding*, as in previous tables. *Distance* is the geographical distance in 1000 km's averaged across all pairwise combinations of all branches of the target and the bidder. *Market Sim.* is the market similarity between the target and the bidder, measured by cosine similarity of the target's and the bidder's county vector, whose jth entry is equal to 1 if the bank is in the corresponding county. *Embedding Sim.* is the cosine similarity between the target's and the bidder's embedding. Standard errors are reported in parentheses, which are clustered at the failed bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

der and a target. *Market Similarity* describes the similarity between the bidder's and target's geographical market coverage. *Embedding Similarity* captures the similarity between the bidder's and target's competitor sets. Detailed variable definitions are in Appendix 1.G. Column (1) shows that more physical distance between target and bidder is correlated with more frequent adoption of LSAs. This is reasonable since physical distance increases information asymmetry, so the bidder tends to face higher uncertainty regarding the true value of the target. Column (2) shows that higher market similarity is correlated with a lower likelihood of utilizing LSAs. This result is also consistent with an information friction interpretation as in Column (1). Bidders operating in a similar market as the target tend to have more information about local market conditions and therefore can better evaluate the target's assets. Hence, these bidders may rely less on the expensive LSAs.

So far the results suggest that high uncertainty about a target's value is associated with a high likelihood of LSA adoption. Following the discussion in Section 1.4.1, receivership duration should also affect LSA utilization; all else equal, longer duration should be associated with lower value uncertainty because time constraints on information processing are relaxed. Columns (5) to (7) show supporting evidence for this hypothesis, reporting regressions including receivership duration and its interaction with the target-bidder relationship variable as regressors. Because receivership duration also largely depends on the complexity of a target, I include other target-level control variables. The results in all Columns (5) to (7) suggest that a longer receivership process is associated with a lower likelihood of utilizing LSAs, consistent with the interpretation that more time for information gathering and processing is helpful for reducing value uncertainty. Moreover, Column (6) suggests that a lengthier receivership can help lower value uncertainty that is due to low market overlap, as evidenced by the positive sign of the interaction term.

1.5 Structural Estimation

1.5.1 The Model

The auction model features a first price format, target heterogeneity, and noisy private signals that are conditionally independent. The model is proposed by Hong and Shum (2002). T targets are auctioned off in a first-price sealed auction format. For any auction t, there are K_t risk-neutral symmetric bidders. Bidder k's valuation $\widetilde{v}_{kt}$ and signal $\widetilde{s}_{kt}$ have the following form,

$$\widetilde{v}_{kt} = Z_t^{\top}\eta + c_t + a_{kt}, \tag{1.1}$$

$$\widetilde{s}_{kt} = \widetilde{v}_{kt} + e_{kt}, \tag{1.2}$$

where Z_t is a vector of target t's characteristics, c_t is the common component of a bidder's valuation of target t not related to its characteristics, and a_{kt} is the bidder-specific component of the bidder's valuation. e_{kt} is the noise embedded in the signals. c_t, a_{kt}, and e_{kt} are assumed to be mutually independent. The information set of a bidder contains $\{\widetilde{s}_{kt}, Z_t, K_t\}$[14]. Bidders solve the following optimization problem to determine their bids,

$$max_b E\left[\left(\widetilde{v}_{kt} - b\right) 1\left\{b > B_{kt}\right\} \middle| \widetilde{s}_{kt}\right], \tag{1.3}$$

where B_{kt} is the maximum opposing bid of bidder k in auction t in equilibrium.

Intuitively, one can think of the common component c_t as reflecting the intrinsic quality of a target's assets, such as the financial conditions of its borrowers. The bidder-specific component a_{kt} can be regarded as the synergies between the target and bidders. A large variation in a_{kt} means bidders have vastly different synergies

[14] Bidders cannot separately observe c and a. The FDIC does not explicitly disclose the number of bidders in each auction, but bidders should have a good enough knowledge of it, as evidenced by the fact that the average bid is weakly increasing in the number of bidders in the auction.

with the targets' assets and operations. For example, one bidder may find the target's loan portfolio particularly valuable because it helps to hedge the risk existing in the bidder's portfolio, or one bidder located near the target can gain market power via the acquisition. The noise term e_{kt} captures the fact that bidders' signals are imperfect, so the role of information quality can be investigated in this setup. The higher the information quality, the lower the variation of noise e_{kt}.. Notice that the noise is bidder-specific, which could reflect bidders' different assessments of the target's common value, or bidders' uncertainty about the exact synergies they have with the target's assets.

1.5.2 Estimation Methodology

The first step of estimating the model is to remove the heterogeneity in the bids due to the heterogeneity in the targets. Haile et al. (2003) shows that additively separable auction heterogeneity in bidder's valuation is preserved in the equilibrium bid function. That is, the bid function $\widetilde{h}(\cdot)$ has the form

$$\widetilde{h}(\widetilde{s}_{kt}; K_t) = \alpha(K_t) + Z_t^{\top}\eta + u_{kt}, \tag{1.4}$$

where $\alpha(K_t)$ is the intercept specific to auctions with K_t bidders.

η can then be estimated by linear regressions of raw bids $\widetilde{b}$ on target characteristics with intercepts specific to the number of bidders in the auctions. Then the homogenized bids are[15]

$$b_{kt} = \widetilde{b}_{kt} - Z_t\widehat{\eta}. \tag{1.5}$$

A homogenized bid b_{kt} is what bidder k would bid for a target t with characteristics $Z_t = 0$. These homogenized bids are then passed to the structural estimation

[15]More details and results related to bid homogenization are in Appendix 1.C.

procedure to estimate the distributions of the common component c, bidder-specific component a, and noise e .

Next, I parameterize the distribution of common component c, bidder-specific component a, and noise e as independent normal distributions. Specifically, I assume $c \sim N(\mu_c, \sigma_c^2)$, $a \sim N(\mu_a, \sigma_a^2)$, and $e \sim N(0, \sigma_e^2)$. It is worth noting that this parametric specification allows for a wide range of valuation and signal configurations. When $\sigma_c = 0$, the auction becomes an independent private valuation auction with noisy signals. When $\sigma_a = 0$, the auction is pure common value. Moreover, when $\sigma_e = 0$, the model features conditionally independent private valuation as studied in Li et al. (2000) and Li et al. (2002). Notice that the μ_c and μ_a cannot be separately estimated, so I let $\mu = \mu_c + \mu_a$, and force $\mu_i = 0$ if $\sigma_i = 0, i \in \{c, a\}$. Therefore, the model is fully characterized by four parameters $(\mu, \sigma_c, \sigma_a, \sigma_e)$.

I then estimate these parameters using the Simulated Method of Moments (SMM) to look for the set of parameters $(\mu, \sigma_c, \sigma_a, \sigma_e)$ that generates the bid moments closest to those observed in the data. More specifically, I use a stochastic optimization algorithm to search for the parameter vector $(\mu, \sigma_c, \sigma_a, \sigma_e)$, such that the first five moments of the equilibrium bid distribution implied by the model are as close as possible to the first five moments of the empirical bid distribution calculated using the homogenized bids. The details of the estimation procedure are described in 1.E.

1.5.3 Estimation Results

The four model parameters $(\mu, \sigma_c, \sigma_a, \sigma_e)$ are estimated to match empirical moments up to the fifth order using a particle swarm algorithm. Table 1.5 reports the estimation results. Panel A reports the point estimates of the four parameters, and their standard errors, which are obtained using the delta method. Panel B reports the model-implied bid moments and their empirical counterparts. All five model moments are within one standard error of the empirical moments. Panel C reports the results of the overidentification test, where the J statistic is 2.6. Since the model has 1 degree of freedom, the p-value is 0.11. Hence, the model with the point estimates cannot be rejected at 10% level. The sizable common component generates affiliation among bidders' valuations, which in turn stresses the necessity of using the affiliated valuation framework. Quantitatively, a typical bidder's valuation, which is the sum of the common and bidder-specific components, has a mean of 0.30 and a standard deviation of 0.09. The signals received by bidders have a mean of 0.30 and a standard deviation of 0.16. Notice here the mean of the signal and value distribution μ is not very informative, as it is for a target with all characteristics equal to zero. To get an idea of the signal and value distribution for an average target, I add back the valuation generated by average target characteristics as in equation 1.1, and get $\hat{\mu} + \bar{Z}^{\top}\hat{\eta} = -0.10$. Intuitively, an average bidder values an average target in failed-bank auctions at 10% discount of its book assets value.

Using the point estimates of the model parameters, I can then solve for the bid functions with different numbers of bidders given the signal and valuation distributions. It is then easy to back out the pseudo-values[16] of the observed bids by plugging them into the inverse bid functions[17]. I plot the inverse bid functions for observed bids as well as the histogram of pseudo-values in Figure 1.1. The pseudo-values are those that correspond to a generic target with average characteristics. Even though all bids are negative, some bidders can be seen to have a positive assessment of the target's assets value, suggesting acquiring the target's assets has a positive estimated-NPV from these bidder's perspective. This result hints that there might be misallocation of a bank's assets even before the failure: if the target bank's assets are owned and operated by the bidders with positive valuation, the target bank might not go into

[16] In the auction econometrics literature, the inverse of the observed bids are called pseudo-values because they are not directly observed, but rather implied by the observed bids in the model. In my framework, the pseudo-values are the signals received by the bidders that can justify their bids.

[17] There are different inverse bid functions for different number of bids. Hence, the tuple of observed bid and the number of bidders in that auction will determine the pseudo-value for that bid.

Panel A: Parameter Estimates			
Parameter	Estimate	S.E.	
μ	0.300	0.006	
σ_c	0.082	0.005	
σ_a	0.040	0.001	
σ_e	0.130	0.012	

Panel B: Homogenized Bid Moments			
Moment Order	Data	S.E.	Model
1	0.2356	0.0042	0.2383
2	0.0610	0.0018	0.0613
3	0.0166	0.0008	0.0167
4	0.0048	0.0003	0.0048
5	0.0014	0.0001	0.0014

Panel C: Overidentification Test			
J-stat	2.6		
p-value	0.11		

Table 1.5: **Baseline Model Estimation Results**: this table reports the structural estimation results for bidder's signal and value distribution. Bidder's valuation for a generic target is $v_{kt} = c_t + a_{kt}$, and the corresponding signal is $s_{kt} = v_{kt} + e_{kt}$, with $c_t \sim N(\mu, \sigma_c^2)$, $a_{kt} \sim N(0, \sigma_a^2)$, and $e_{kt} \sim N(0, \sigma_e^2)$. The estimates are obtained using SMM that matches the model and empirical homogenized bid moments up to sixth order. Panel A reports the point estimates and their standard errors of these distribution parameters. Panel B reports the model moments of bids when the signals are generated from the distribution in Panel A, with their empirical counterparts. Panel C reports the results for the overidentification test, which tests for whether the model and empirical moments are statistically different.

resolution in the first place. Though beyond the scope of this paper, it would be interesting to investigate how such misallocation occurs and why it is not corrected in the regular bank M&A market before the target banks go into the receivership process.

I also compute the expected winner's valuation and bid given the estimated valuation and signal distribution. The former characterizes the total value creation in these auctions, and the latter characterizes the auction revenue. The results are plotted in Figure 1.2, where the horizontal axis is the number of bidders in an auction, and the vertical axis is the winner's valuation or bid relative to the average liquidation value of the target's assets[18]. The results indicate that the auctions in the sample are extremely valuable compared with the liquidation alternative from both value creation and auction revenue perspectives. The winner's valuation is expected to be over 36% higher, and the winner's bid is expected to be over 30% higher than the historical average liquidation value.

1.6 Analysis

1.6.1 Information Quality, Resolution Cost, and Allocative Efficiency

Bidders' information in failed-bank auctions has two major sources. The first and more important source is the FDIC disclosures made to all potential acquirers once they sign confidentiality agreements. The FDIC collects this information once a failed bank enters the resolution process. The second potential source is bidders' due diligence in which their personnel visits the failed bank to gather additional information. The time-sensitive nature of the resolution process and the need to

[18] According to Bennett and Unal (2015), the historical average liquidation value of assets relative to the book value is about 67%.

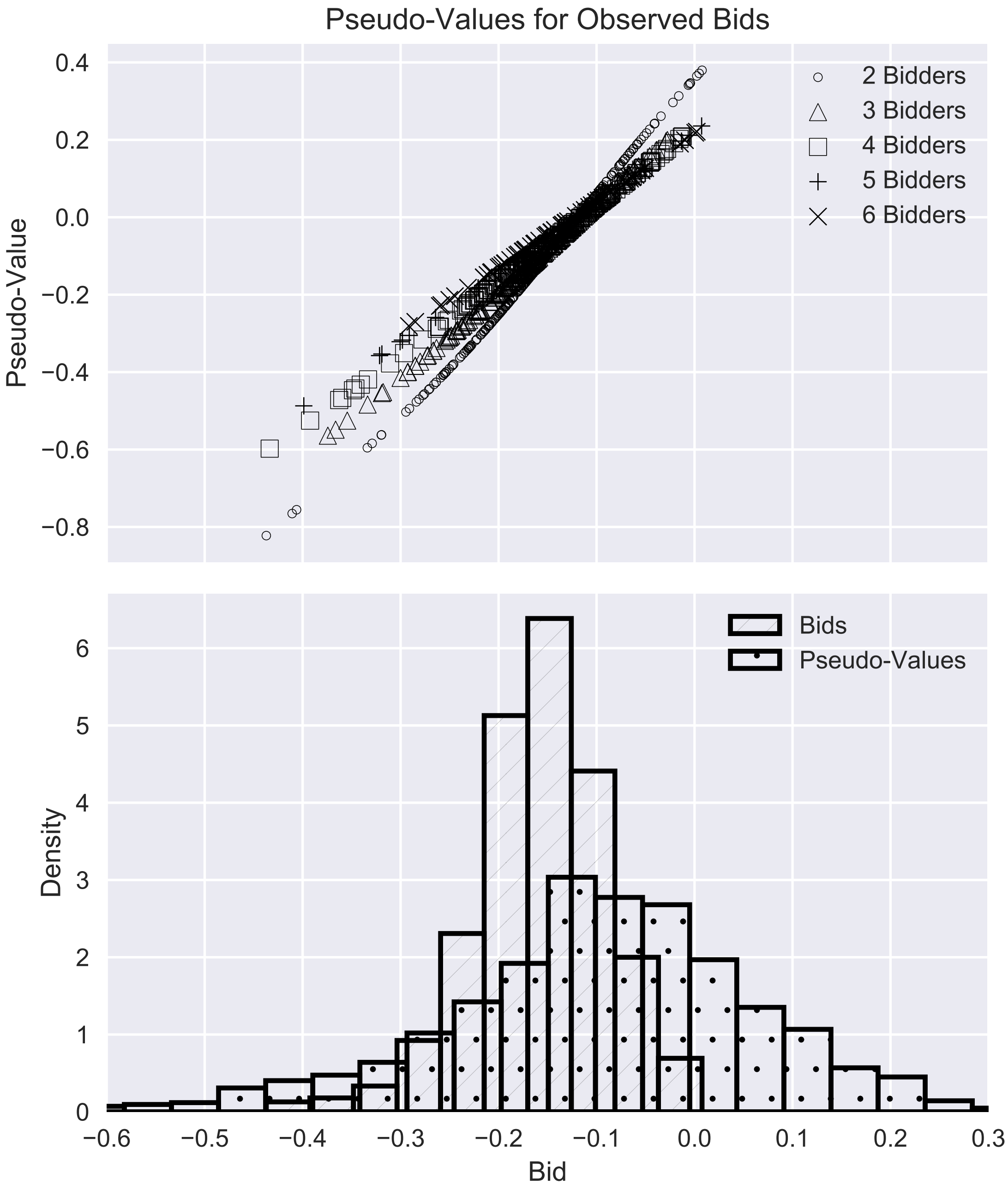

Figure 1.1: **Pseudo-Values and Observed Bids**: this figure plots the pseudo-values of the observed bids obtained by inverting the bid functions under the signal distributions at the estimated parameter values in Table 1.5. The top graph plots the inverse bid functions for different numbers of bidders in the auction. The bottom graph plots the histogram of the observed bids and the pseudo-values. The horizontal axis is the bid measured by the premium as a percentage of the book assets of the target. The vertical axis in the top graph is the pseudo-value measured by the premium as a percentage of the book assets of the target.

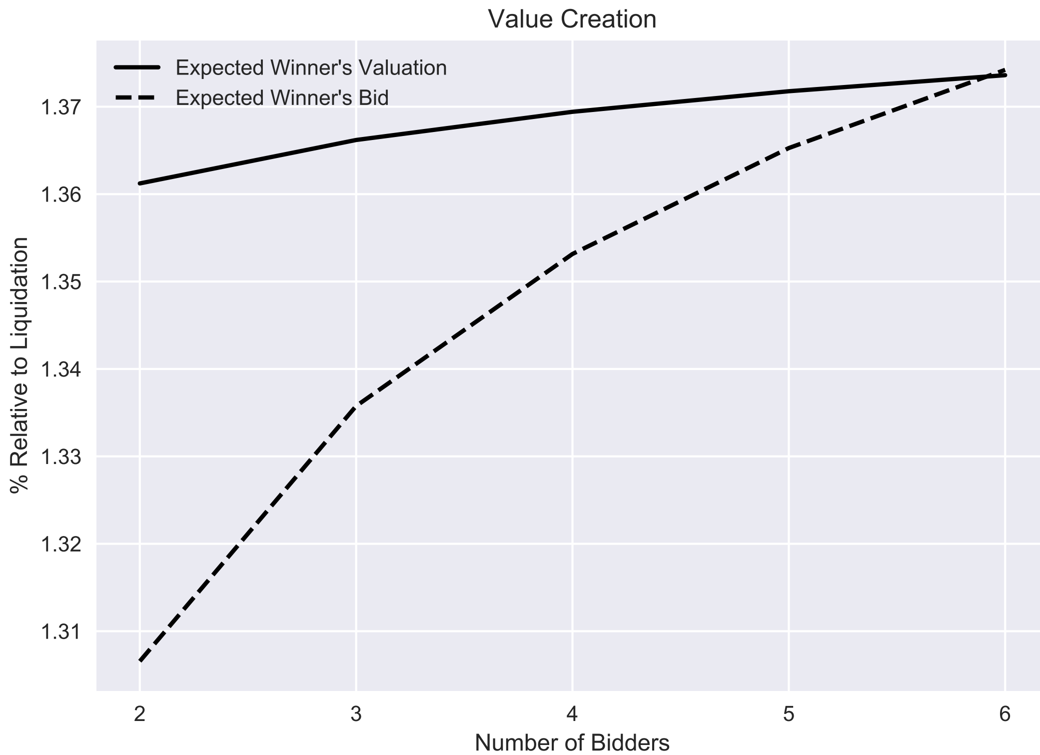

Figure 1.2: **Value Creation and Auction Revenue**: this figure plots the expected winner's valuation against the number of bidders in the auction, under different noise levels, where the valuation and signals have the relationship $v_{it} = s_{it} + e_{it}$. The vertical axis represents the expected winner's valuation scaled by the average liquidation value of the assets. v_{it} is the bidder's true (ex-post) valuation, which cannot be identified directly. s_{it} is the bidder's signal, whose distribution is estimated and reported in Table 1.5. e_{it} is the normally distributed noise in the signals with mean 0 and standard deviation σ_e, independent across bidders and auctions, and is independent of s_{it}. For a given σ_e, I simulate a large sample of signals s_{it} from the estimated distribution. The bidder with highest s_{it} in each auction wins. Then I simulate noise e_{it} of the same sample size, and compute the true valuation by adding up s_{it} and e_{it}. The expected winner's valuation is computed by averaging v_{it} across all winners in all simulated auctions.

speed up information collection create a concern about information quality. After approval of on-site visits, bidders usually get 4 to 6 days for the visits (Granja et al., 2017), which is considerably shorter than the due diligence period in regular M&A transactions.

A potential free-rider problem in the due-diligence process also creates concerns about information quality in these auctions. It is the FDIC's practice to share all information gathered in the due diligence process among all participating bidders[19], which discourages bidders from exerting due diligence effort in the first place. Bidders may wait for the information collected by others, because any bidder performing due diligence is bearing the full cost but not enjoying all the benefit. This free-rider problem could be a critical reason for the low utilization of on-site due-diligence documented in Granja et al. (2017).

Noisy signals in these auctions create misallocation since the target is not always allocated to the bidder with the highest valuation but rather to the bidder with the highest signal. The misallocation is more severe when signals contain more noise, which is likely to be the case when multiple simultaneous failures occur, and the FDIC only has limited resources to cover each of the failures.

In my setting, I can quantify the marginal effect of improving information quality on both value creation and auction revenue by measuring the improvement in expected winner's valuation and expected winner's bid from a reduced signal noise. To reach this assessment, I conduct the following experiment. The estimate of signal distribution describes the current information quality in failed-bank auctions. I then compute the percentage increase in the expected winner's valuation by marginally reducing the standard deviation of noise σ_e by 1%. There will be less misallocation under the improved signal since signals better reflect the valuation. The results

[19]The FDIC states in the Resolution Handbook that all potential bidders performing due diligence are provided the same information so that no one potential bidder has an advantage. Questions posed by one bidder are answered and provided to all bidders.

are presented in the top graph of Figure 1.3. The horizontal axis is the number of bidders in an auction. The vertical axis is the percentage change in expected winner's valuation and expected winner's bid as the result of signal improvement, relative to the winner's valuation with the unimproved signal. The slashed bars show the impact on value creation of noise reduction is quantitatively substantial: a 1% decrease in the noise standard deviation can lead to a 0.7% to 1.5% increase in the value creation, depending on the number of bidders in the auction, which corresponds to around \$0.6 to \$1.3 billion for all the failed banks in my sample. It is also intuitive to see the marginal benefit of improving information quality increases with the number of bidders in the auction, since with more bidders, it is more likely the target gets misallocated to a bidder without the highest valuation.

The marginal benefit of improving information quality regarding value creation is substantial, which begs the question of why there is such a level of unrealized benefit. Recall that the FDIC is bound by the Least Cost Resolution policy, meaning the FDIC is more concerned about the highest bid received in each auction, a crucial determinant of resolution cost, than about the value creation of the auctions. Hence, understanding the FDIC's incentive requires assessing the marginal effect of improving information quality on the winner's bid instead of valuation. The Least Cost Resolution policy, in this case, may hinder the FDIC's incentive to improve information quality if the benefit does not accrue to the agency through winning bids. In this auction environment, the effect on bids of improving information quality, or reducing the noise, is theoretically ambiguous, dependent on the relative magnitudes of all the components in the bidders' signals, as well as on the level of competition in the auction. On the one hand, lower noise can lead to more aggressive bidding since the concern about winner's curse is lower. On the other hand, lower noise also mechanically leads to a lower winner's signal on average. Therefore, the marginal effect of improving information quality on bids remains an empirical question that

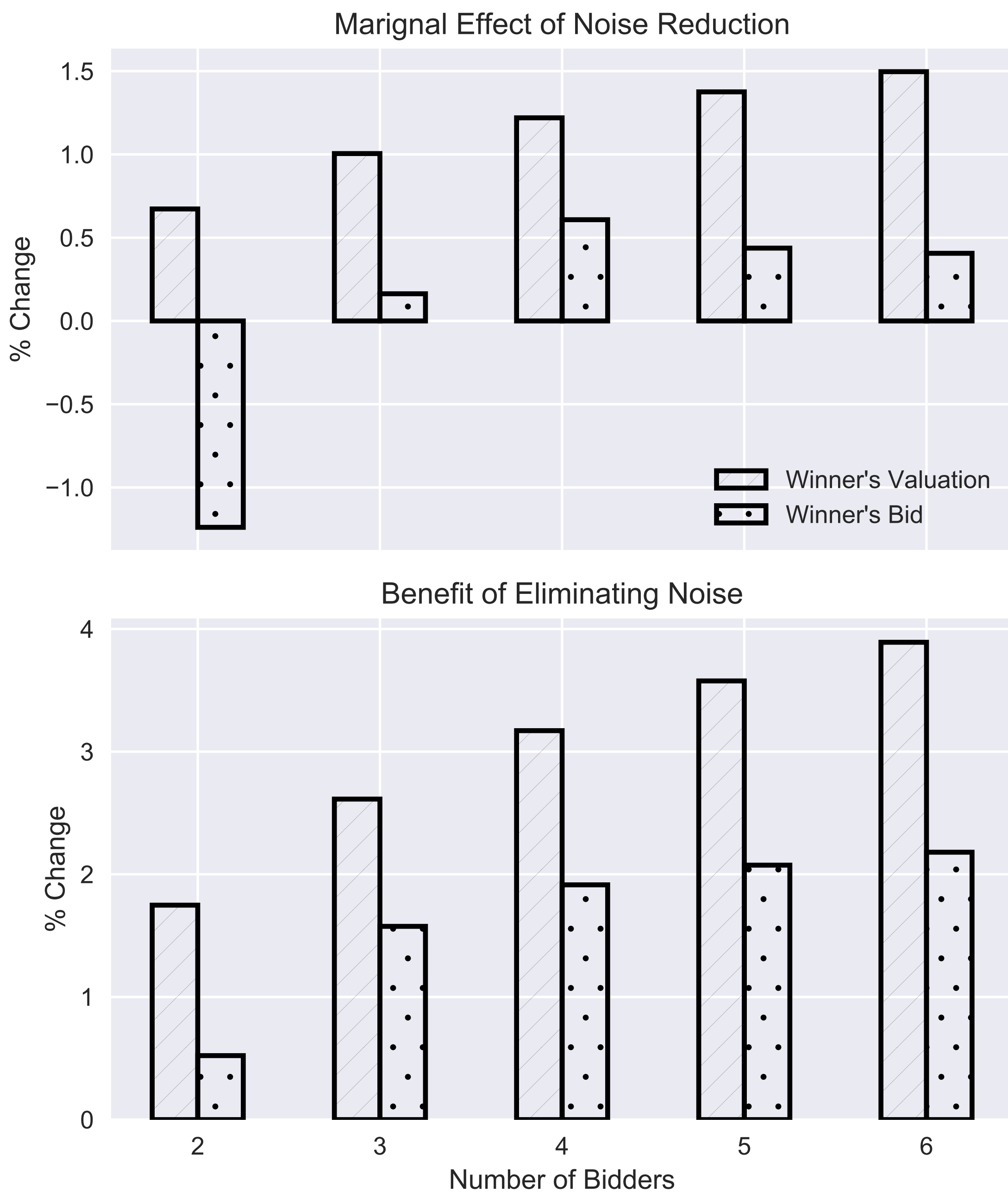

Figure 1.3: **Effects of Signal Noise Reduction**: this figure plots the effects of noise reduction on the expected winner's valuation and bid, relative to the benchmark case in Table 1.5. The top graph shows the marginal change in the expected winner's valuation or bid as the result of a 1% reduction in the noise standard deviation σ_e. The bottom graph shows the change in the expected winner's valuation or bid as the result of setting noise standard deviation σ_e to 0.

I can quantify using the structural estimates obtained above. The top graph of Figure 1.3 also plots in dotted bars the marginal change in expected winner's bid, or the FDIC's auction revenue, as a result of a marginal reduction in noise standard deviation. Immediately noticeable is that the increase in the FDIC's revenue is small, both relative to the increase in winner's valuation and in absolute terms, suggesting that the FDIC has a much weaker incentive to improve information quality if revenue is the agency's main concern than if value creation were the main objective. Moreover, the plot reveals that in a two-bidder auction, the marginal effect of improving information quality on the FDIC's revenue is, in fact, negative, which essentially prevents the FDIC from making any marginal policy effort to improve information quality.

So far I have shown that improving information quality is not in the FDIC's best interest on the margin from a revenue standpoint. However, the bottom graph of Figure 1.3 suggests that the benefit on winning bids of completely eliminating noise is in no way negligible: the winning bids are expected to be 1% to 2% higher after noise is eliminated. One interpretation of the result is that the FDIC may face a significant cost in eliminating noise which leaves the benefit above unrealized. I find suggestive evidence that the resource constraint faced by the FDIC during the peak of failures may be an important contributor for such cost. Specifically, I find that receivership duration is strongly negatively associated with the number of simultaneous failures, which suggests that the FDIC may have to cut each resolution short because of resource constraints when there are many bank failures at the same time.

1.6.2 Participation and Information Quality

In this section, I demonstrate how information quality affects the effectiveness of more participation as an approach to enhance efficiency in failed-bank auctions. Standard private value auction models suggest that participation is in general beneficial for both value creation and auction revenue. The basic intuition is that the maximum valuation among three bidders is on average higher than the maximum valuation among two bidders. Meanwhile, bidders also bid more aggressively when there are more competitors. Hence, it is beneficial to have more bidders in the auctions from the perspectives of both value creation and auction revenue. In the context of failed-bank auctions, encouraging participation has also been an important policy focus to increase winning bid and reduce resolution cost. It is worth noting that the noisy signals in failed-bank auctions add some twist to the intuition above. When bidders are facing noisy signals, additional participation leads to not only benefit, but also misallocation cost: more bidders will result in a higher probability of the highest valuation bidder not winning the auction, compared with an auction with fewer bidders. In other words, auctions with more bidders are on average less efficient than auctions with fewer bidders regarding allocation.

To quantify the effects of participation in the presence of noisy signals, I conduct the following exercise. I denote $E\left[y^{(1)}\middle| e, N\right]$ as the expected winner's valuation given the distribution of signal noise e and the number of bidders in the auction N. $y^{(1)}$is the winner's valuation or bid. Now the net benefit of one additional bidder can be written as follows,

$$E\left[y^{(1)}\middle| e, N+1\right] - E\left[y^{(1)}\middle| e, N\right] \tag{1.6}$$

$$=E\left[y^{(1)}\middle| 0, N+1\right] - E\left[y^{(1)}\middle| 0, N\right] \tag{1.7}$$

$$-\left[\left(E\left[y^{(1)}\middle| 0, N+1\right] - E\left[y^{(1)}\middle| e, N+1\right]\right) - \left(E\left[y^{(1)}\middle| 0, N\right] - E\left[y^{(1)}\middle| e, N\right]\right)\right] \tag{1.8}$$

The equation above decomposes the net change of one more bidder on winning valuation and bid into two components: the participation effect $E\left[y^{(1)}\middle| 0, N+1\right] - E\left[y^{(1)}\middle| 0, N\right]$ and the change in misallocation effect $\left(E\left[y^{(1)}\middle| 0, N+1\right] - E\left[y^{(1)}\middle| e, N+1\right]\right) - \left(E\left[y^{(1)}\middle| 0, N\right] - E\left[y^{(1)}\middle| e, N\right]\right)$. Concretely, the term $E\left[y^{(1)}\middle| 0, N+1\right] - E\left[y^{(1)}\middle| 0, N\right]$ measures the change in the winning valuation or bid if bidders receive perfect signals.

Meanwhile, the misallocation becomes more severe with more bidders with noisy signals, since the chance of the highest-value bidder winning the auction is lower. The change in the winning valuation or bid due to this increased misallocation is captured by $\left(E\left[v^{(1)}\middle|\, 0, N+1\right] - E\left[v^{(1)}\middle|\, e, N+1\right]\right) - \left(E\left[v^{(1)}\middle|\, 0, N\right] - E\left[v^{(1)}\middle|\, e, N\right]\right)$. The difference between the participation effect and the misallocation effect measures the net effect of having one additional bidder in the auction.

It is helpful to establish some qualitative intuition for the expected results of this exercise. The net effect of participation on winner's valuation should be positive (or at least nonnegative). That is, the participation effect should always dominate the misallocation effect on winner's valuation. To gain an intuition for this hypothesis, consider an extreme case with noise's standard deviation equal to infinity. In this case, the increase in misallocation due to one more participating bidder is the largest. It is easy to see this situation is equivalent to choosing the winner among bidders randomly, so every bidder has an equal chance of winning the auction, regardless of their true valuation. So the expected winner's valuation is always the unconditional mean of the bidder's valuation distribution, which is invariant with the number of bidders in the auction. Hence, adding one additional bidder generates exactly the same level of winner's valuation as that without the additional bidder. With even just barely informative signals, one additional bidder should lead to an increase in expected winner's valuation.

The net effect of participation on winner's bid is, again, theoretically ambiguous. Additional bidders in an auction generate three competing forces on the winning bid simultaneously. First, more bidders mechanically lead to an increase in the winning signal on average, which should lead to a higher winning bid if the bid function does not change with the number of bidders. Second, more bidders can also lead to less aggressive bidding out of concern for winner's curse, which can lead to a lower bid for the received signal, so the winning bid could be lower as well. Third, more bidders may lead to more competition among bidders due to the existence of the bidder-specific valuation component, which eventually leads to more aggressive bidding. Which force dominates the others crucially depends on the relative magnitudes of the valuation components, the noise level, and the number of bidders in the auction. The framework in this paper and the structural estimates obtained in Section 1.5.3 can help empirically measure the net effect of participation on winner's bid, thus providing insights on the FDIC's incentive to promote participation.

Figure 1.4 shows the decomposition results. The horizontal axis is the number of existing bidders in an auction, and the vertical axis shows the percentage change in expected winner's valuation or bid by introducing one more bidder into the auction, relative to the winner's valuation without that additional bidder. The participation benefit, in slashed bars, still clearly dominates misallocation cost, in dotted bars, with the presence of noisy signals, resulting in a positive net benefit of an additional bidder in the auction. Concretely, the black line shows introducing one more bidder to a two-bidder auction can increase value creation by about 0.4%, or about $5 million for an average failed bank. The result suggests that encouraging participation is in general beneficial to the total value creation, but the benefit is quite small in absolute terms A much more salient observation from the plot is that the value increase can be three times as much if the noise is eliminated, highlighting the fact that signal noise is drastically hurting the value effect of more participation. The dashed line shows that the benefit of more participation on the winning bid is massive: the winning bid is expected to be over 2% higher with one additional bidder in a two-bidder auction. The contrast between the benefit of participation on winner's valuation and winner's bid reveals a potential overinvestment in policy effort to promote participation, which can happen when the cost of promotion is lower than its benefit for winner's bid but higher than its benefit for winner's valuation.

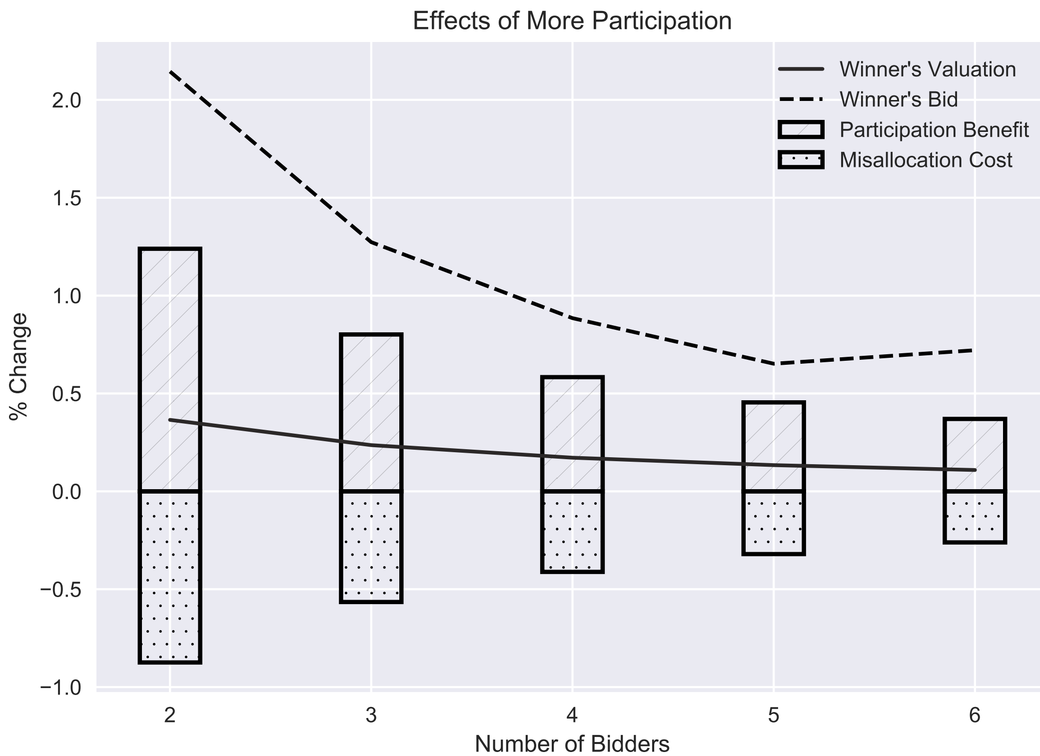

Figure 1.4: **Effects of Participation with Noisy Signals**: this figure plots the decomposition of the effect of one additional bidder on the expected winner's valuation and bid. The black curve represents the net benefit of one additional bidder on value creation, measured as the change in expected winner's valuation relative to the case without that additional bidder. The dashed curve represents the net benefit of one additional bidder on auction revenue, measured as the change in expected winner's bid relative to the case without that additional bidder. The slashed bars represent the benefit of one additional bidder on the expected winner's valuation if there is no noise in bidders' signals. The dotted bars represent the increase in misallocation cost due to one additional bidder with noisy signals.

The results also highlight the complementarity between participation and information quality in improving value creation in these failed-bank auctions. This complementarity suggests that the FDIC should spend effort on both encouraging participation and enhancing information quality at the same time to more effectively improve value creation in these auctions.

1.6.3 Flexible Loss Share Agreements and Information Quality

LSAs are used to encourage whole bank transactions in failed-bank auctions, so the FDIC does not have to retain any assets in the receivership for later liquidation(Cowan and Salotti, 2015).

As discussed in Section 1.2.2, LSAs were introduced in the early 1990s, and have been through some changes since then. Most notably, in the wave of clustered bank failures during the most recent financial crisis, the FDIC allowed for more flexibility in LSA terms for failed banks with book assets over $500 million. Before this policy change, bidders could only choose whether or not to have an LSA with mostly standard terms. Following this policy change, about 50% of bids for targets over $500 million feature nonstandard loss share percentages.

The exact theoretical consequences of introducing such flexibility in an auction setting command further research. However, some simple intuition on the effect of LSA flexibility on bidders' valuation distribution can be gained. On the one hand, with flexible LSAs, bidders pooling under the same loss share rules may be more similar to one another than they would be absent flexible LSAs. These bidders are then likely to have less dispersed valuation and signals about a target. On the other hand, the LSA flexibility may bring in a new set of bidders who find pooling with other bidders under the standard loss share rule so costly that they do not participate in the auctions at all. The new set of bidders may enlarge the dispersion of bidders' valuation and signals. The two opposite forces above lead to an ambiguous change in the signal and value distribution, and further the expected winning bid and valuation. Therefore, the actual effect of LSA flexibility remains an empirical question on which the structural estimates can shed some light.

To characterize the effect of LSA flexibility, I first separately estimate the signal distributions for auctions with and without flexible LSA terms. Second, I show the impact of flexibility on value creation and auction revenue with the presence of noisy signals through some counterfactual simulations.

To estimate how bidder's value and signal distribution differ with and without flexibility in the terms of LSAs, I allow the value and signal distribution parameters to be different for targets above and below the \$500 million threshold. The value distribution parameters are given by $(\mu_0, \sigma_{c0}, \sigma_{a0}, \sigma_{e0})$ for bidders in auctions for targets below \$500 million, and $(\mu_1, \sigma_{c1}, \sigma_{a1}, \sigma_{e1})$ otherwise. The estimation procedure is the same as that for the baseline model described in Section 1.5.2. $(\mu_0, \sigma_{c0}, \sigma_{a0}, \sigma_{e0})$ is estimated using the subsample of 665 bids for targets below \$500 million in book assets, and $(\mu_1, \sigma_{c1}, \sigma_{a1}, \sigma_{e1})$ is estimated using the subsample of 105 bids for targets over \$500 million in book assets.

Table 1.6 reports the estimation results. The estimates for μ_0 and μ_1 indicate the bidders in auctions with and without flexible LSAs have similar average valuation after controlling for all available target heterogeneity including the actual loss share percentage of the bids. Most noticeably, bidders' valuation under flexible LSAs has a less dispersed common component and a more dispersed bidder-specific component than that under inflexible LSAs.

Given the distribution estimates obtained above, the following decomposition can assess the value effect of flexible LSAs over inflexible LSAs and its complementarity

Panel A: Parameter Estimates				
	Inflexible LSA		Flexible LSA	
Parameter	Estimate	S.E.	Estimate	S.E.
μ	0.310	0.017	0.304	0.015
σ_c	0.080	0.007	0.048	0.005
σ_a	0.031	0.013	0.063	0.002
σ_e	0.119	0.010	0.078	0.011

Panel B: Homogenized Bid Moments						
Moment Order	Data	S.E.	Model	Data	S.E.	Model
1	0.2327	0.0160	0.2492	0.2492	0.0118	0.2591
2	0.0608	0.0063	0.0666	0.0656	0.0057	0.0697
3	0.0167	0.0022	0.0188	0.0179	0.0024	0.0194
4	0.0049	0.0007	0.0055	0.0051	0.0009	0.0056
5	0.0015	0.0002	0.0017	0.0015	0.0004	0.0016

Panel C: Overidentification Test		
J-stat	2.5	2.1
p-value	0.11	0.15

Table 1.6: **Loss Share Flexibility and Valuation Distribution**: this table reports the structural estimation results for signal distributions under flexible and inflexible LSAs. Bidder's valuation for a generic target is $v_{kt} = c_t + a_{kt}$, and the corresponding signal is $s_{kt} = v_{kt} + e_{kt}$, with $c_t \sim N\left(\mu_f, \sigma_{cf}^2\right)$, $a_{kt} \sim N\left(0, \sigma_{af}^2\right)$, and $e_{kt} \sim N\left(0, \sigma_{ef}^2\right)$, $f \in \{0, 1\}$. $f = 0$ corresponds to inflexible LSAs, and $f = 1$ corresponds to flexible LSAs. The estimates are obtained with two subsamples of bids: one for targets over \$500 million in book assets, and one for targets below \$500 million in book assets, using SMM that matches the model and empirical homogenized bid moments up to sixth order. Panel A reports the point estimates and their standard errors of these distribution parameters. Panel B reports the model moments of bids when the signals are generated from the distribution in Panel A, with their empirical counterparts. Panel C reports the results for the overidentification test, which tests for whether the model and empirical moments are statistically different.

with information quality, similar to the analysis in Section 1.6.2

$$\begin{aligned}
& E\left[y^{(1)}\middle| c_f, a_f, e_{inf}, N\right] - E\left[y^{(1)}\middle| c_{inf}, a_{inf}, e_{inf}, N\right] \\
=& E\left[y^{(1)}\middle| c_f, a_f, 0, N\right] - E\left[y^{(1)}\middle| c_{inf}, a_{inf}, 0, N\right] \\
-& \left[\left(E\left[y^{(1)}\middle| c_f, a_f, 0, N\right] - E\left[y^{(1)}\middle| c_f, a_f, e_{inf}, N\right]\right)\right. \\
& \left. - \left(E\left[y^{(1)}\middle| c_{inf}, a_{inf}, 0, N\right] - E\left[y^{(1)}\middle| c_{inf}, a_{inf}, e_{inf}, N\right]\right)\right]
\end{aligned}$$

where $y^{(1)}$ is the winning bidder's valuation or bid. $E\left[y^{(1)}\middle| c_f, a_f, 0, N\right] - E\left[y^{(1)}\middle| c_{inf}, a_{inf}, 0, N\right]$ is the effect of flexible LSAs in a perfect information environment. The basic idea is that bidders valuation distribution changes because their choice sets regarding the loss share percentage under flexible LSAs expand. So the common component changes from c_{inf} to c_f, and the bidder-specific component changes from a_{inf} to a_f for the bidders that are initially under the inflexible LSAs. $\left(E\left[y^{(1)}\middle| c_f, a_f, 0, N\right] - E\left[y^{(1)}\middle| c_f, a_f, e_{inf}, N\right]\right) - \left(E\left[y^{(1)}\middle| c_{inf}, a_{inf}, 0, N\right] - E\left[y^{(1)}\middle| c_{inf}, a_{inf}, e_{inf}, N\right]\right)$ captures the change in misallocation effect due to the additional flexibility in LSAs. Notice here I assume that LSA flexibility does not directly affect information quality, as the signal noise is still e_{inf} even when the LSAs are flexible. A negative change means that the value distribution induced by LSA flexibility is, in fact, less prone to the misallocation problem caused by noisy signals. The approach to compute these quantities with the estimates above is the same as in Section 1.6.2.

Figure 1.5 shows the decomposition results. The horizontal axis represents the number of bidders in an auction, and the vertical axis is the percentage change in the expected winner's valuation or bid relative to the expected winner's valuation with inflexible LSAs. The black line shows that the flexibility in LSAs in total leads to around a 1% to 2% increase in the expected winner's valuation for auctions with two to six bidders. Recall that the average valuations under flexible and inflexible LSAs are statistically similar. Hence, the increase in value creation as a result of LSA

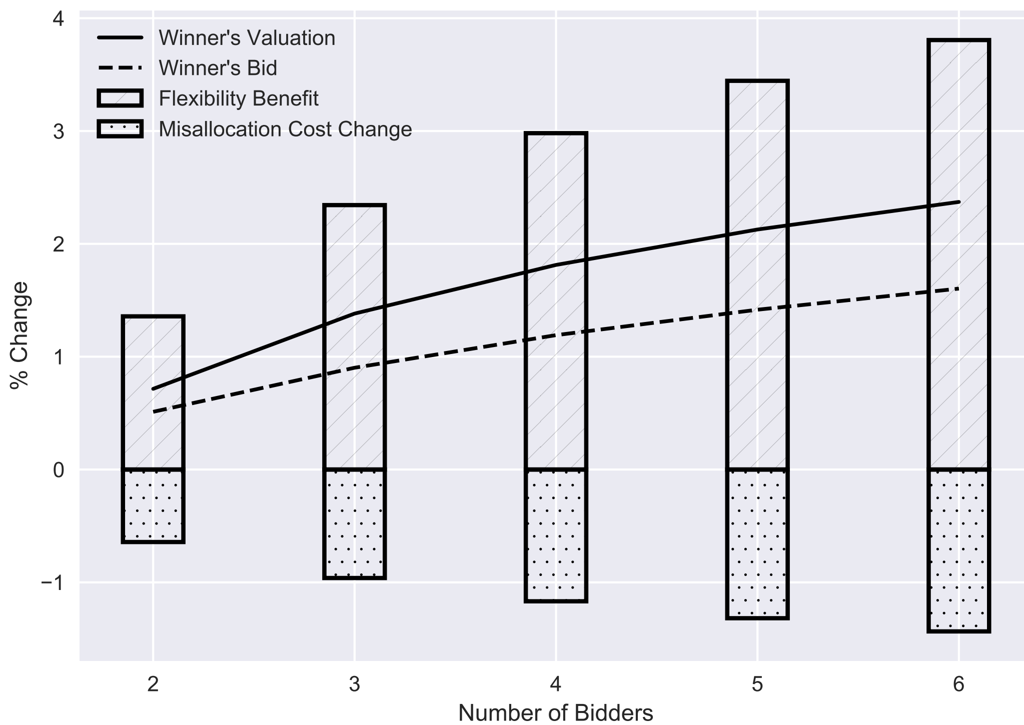

Figure 1.5: **Effects of Flexible LSAs**: this figure plots the decomposition of the effect of flexible LSAs on the expected winner's valuation, relative to inflexible LSAs. The black curve represents the net benefit of LSA flexibility on value creation, measured as the change in expected winner's valuation relative to the case with inflexible LSAs. The dashed curve represents the net benefit of LSA flexibility on auction revenue, measured as the change in expected winner's bid relative to the case with inflexible LSAs. The slashed bars represent the benefit of LSA flexibility on the expected winner's valuation if there is no noise in bidders' signals. The dotted bars represent the drop in misallocation cost due to the change in signal distribution as a result of LSA flexibility.

flexibility is entirely due to its effect on the dispersion of the valuation components. The dotted bars in the graph indicate that the LSA flexibility, in fact, escalates misallocation, given the same noise distribution. The benefit of LSA flexibility on winner's valuation can be over 50% higher if noise is eliminated, shown by the slashed bars. This result suggests that information quality largely complements the value effect of flexible LSAs. The dashed line in the graph shows the effect of LSA flexibility on expected winner's bid. It is clear that allowing for flexible LSAs is most valuable for auctions with more bidders from an auction revenue perspective. This finding is consistent with the fact that the FDIC only allows for flexible LSAs in auctions for larger targets, which tend to attract more bidders. However, this result also suggests that granting flexibility based explicitly on the number of bidders in an auction, rather than the size of the target, may be a more effective way to exploit the benefit of LSA flexibility. The plot shows that the benefit of LSA flexibility for winner's bid is significantly lower than that for the winner's valuation, indicating that the FDIC might be reluctant to offer flexible LSAs from a pure auction revenue standpoint. However, the benefit to winner's bid is still sizable, suggesting there might be a high administrative cost associated with offering flexible LSAs, given recent discussion of the FDIC phasing out LSAs altogether (Archer, 2012).

1.6.4 Bidder Characteristics and Valuation

The pseudo-values obtained earlier in Section 1.5.3 also provide a special lens for investigating how bidders' characteristics affect their valuation of targets. Moreover, the variation in these bidder characteristics within and across auctions has important implications for value creation and auction revenue in this environment. Conceptually, the pseudo-values (true values measured with unbiased noise) can be regressed on bidder characteristics. This analysis cannot be done by directly looking at how bids covary with bidder characteristics because bids are confounded by competitiveness in the auctions. This is also hard to do with other data on M&As because usually one cannot see all bidders and all bids.

However, the analysis is still challenging for two reasons: firstly, only a small fraction of the pseudo-values can be matched with bidders because the FDIC deliberately withholds the correspondence between bids and bidder identities for all but the top two bids; secondly, the pseudo-values contain a common component of each auction that is unobservable. Fortunately, the FDIC does disclose the identities of all bidders in each auction. With the help of Full Information Maximum Likelihood (FIML) estimation with Expectation Maximization (EM) algorithm, the two challenges mentioned above can still be addressed to estimate how bidder characteristics affect their signals, and equivalently valuations.

To demonstrate the basic idea of the approach, I assume the noisy signals and the bidder characteristics have the following relationship

$$\widetilde{s}_{kt} = \alpha + c_t + \widetilde{X}_{kt}^{\top}\beta + u_{kt}$$

where k indexes bids, and t indexes targets.. $\widetilde{X}_{kt}$ is a vector of characteristics of the bidder who submits the bid. The residual term u_{kt} is assumed to be normally distributed with mean 0 and standard deviation σ. For illustration purposes, suppose now all variables except for c_t are observable.

The observed common component c_t can be removed by demeaning both sides of the equation above, to obtain the following regression equation

$$s_{kt} = X_{kt}^{\top}\beta + u_{kt}$$

where $s_{kt} = \widetilde{s}_{kt} - \frac{1}{K_t}\sum_{k=1}^{K_t}\widetilde{s}_{kt}$ and $X_{kt} = \widetilde{X}_{kt} - \frac{1}{K_t}\sum_{k=1}^{K_t}\widetilde{X}_{kt}$. This transformation removes the unobserved common component from the regression equation.

However, the problem remains that the characteristics $\widetilde{X}_{kt}$ cannot be observed for the bids not matched with bidders. Only 112 out of 882 bids can be explicitly matched with their bidders. Even if I only implement the estimation on the matched sample, the coefficient estimates are biased since the matched sample consists of only the top two bidders. The particular data structure in this setting where the full sets of bidders are observed for all auctions allows for the estimation of the coefficients with FIML, using the EM algorithm. It is worth pointing out that this estimation approach does not require any more assumptions than MLE does. The basic idea of this estimation procedure is that the missing bidders can be replaced by "synthetic" bidders that are the weighted average of all participating bidders in the given auction. The weights of different participating bidders come from the probability of these participating bidder having the pseudo-values with missing bidder's identity. Intuitively, the EM estimation algorithm starts with a random guess of β and σ, using the guess to compute the probability of participating bidders having the pseudo-values with missing bidder identities in all auctions. Then the probability is used to construct the "synthetic" bidders to replace the missing bidders. Now, without any missing bidders, the estimates for β and σ are updated using standard MLE. The normality assumption of the residual term u is not necessary in principle. However, the estimators, as well as standard errors, can be largely obtained in closed form under this parametric assumption, which makes the estimation computationally feasible. The details of the EM estimation algorithm and related derivations are in Appendix 1.F.

Table 1.7 reports the EM estimation results on how the characteristics of bidders affect their valuation. The dependent variable is the pseudo-value for all columns. Independent variables include some financial variables constructed from the Call Reports and some measures of similarity between bidders and targets. Column (1) shows the relationship between pseudo-values and Call Reports variables. Column

	Dependent Variable: Pseudo-Value					
	(1)		(2)		(3)	
Variables	Est.	S.E.	Est.	S.E.	Est.	S.E.
Equity Ratio	0.127	0.106			0.159	0.105
Loan Ratio	-0.205***	0.035			-0.165***	0.035
%Residential	-0.046	0.039			-0.134***	0.048
%C&I	0.137**	0.061			0.099	0.064
OREO Ratio	-1.499***	0.399			-1.337***	0.400
Loan Earn	8.959**	3.863			6.267	3.950
NPL Ratio	-1.757*	0.999			1.536	1.008
ROA	-1.300***	0.482			-0.649	0.491
Liquidity Ratio	-0.227*	0.128			-0.306***	0.128
Size	0.017***	0.004			0.016***	0.004
Age	-0.002	0.004			-0.000	0.004
ΔHHI			0.112	0.507	0.022	0.498
Loan Sim.			0.058**	0.025	0.063***	0.031
Distance			-0.003***	0.001	-0.004***	0.001
Market Sim.			0.002	0.026	0.048*	0.026
Embedding Sim.			-0.055**	0.028	-0.063**	0.027
$\# Pseudo - Values$	882	882	882	882	882	882
$\# Participating\ Bidders$	834	834	834	834	834	834

Table 1.7: **Valuation and Bidder Characteristics**: this table reports the Full Information Maximum Likelihood estimation results of the model $s_{it} = X_{it}'\beta + u_{it}$, where s_{it} is the pseudo-value obtained by inverting the bid functions at the observed bids, X_{it} is the characteristics of bidder i in auction t, and u_{it} is normally distributed with mean 0 and standard deviation σ. ΔHHI is the average change in HHI in the bidder's market if it were to win the auction. *Loan Similarity* is the cosine similarity of the target's and bidder's loan portfolio, which is measured by a vector of weights in different loan categories. *Distance* is the geographical distance averaged across all pairwise combinations of all branches of the target and the bidder. *Market Sim.* is the market similarity between the target and the bidder, measured by cosine similarity of the target's and the bidder's county vector, whose jth entry is equal to 1 if the bank is in the corresponding county. *Embedding Sim.* is the cosine similarity between the target's and the bidder's embedding. Standard errors are reported in the parentheses. *, **, *** denote significance at 10%, 5%, 1% respectively.

(2) shows the correlation between pseudo-values and variables capturing bidder-target relationships, and Column (3) includes all the variables. Some robust relationships are observed in all columns. Bidders with higher loan-to-asset and OREO ratios tend to value targets lower, which may indicate that these bidders have capitalization concerns about acquiring these extremely undercapitalized targets so they demand higher capital injection from the FDIC. Also, I find that the larger bidders have a higher valuation.

Bidder's valuation does not seem to depend on the potential market power change of a transaction, as evidenced by the insignificance of variable ΔHHI. HHI is computed using the share of deposits at the county level, and the change in HHI for a bidder is the equally weighted average of changes in HHI in all counties the bidder is in. The effect remains qualitatively the same when I compute the deposit-weighted average change in HHI across the bidder's market. The result could be due to the anti-trust restrictions on these transactions: a transaction is unlikely to go through if it generates sufficient anti-trust concerns. Several times in the past the Department of Justice has stepped into failed-bank transactions and required the acquirer to sell branches to ensure that the acquirer does not become a de facto monopoly in some regions.

Bidders closer to targets and with more similar loan portfolios have higher valuations of the targets, which is consistent with an information asymmetry explanation. These bidders tend to have better information about the targets' value due to either geographical proximity or similar asset composition. Granja (2013) and Granja et al. (2017) also document consistent phenomenon that bidders closer to the targets are more likely to participate and win the auctions. It is interesting to see some evidence that bidders in less similar markets and with less similar competitor sets tend to value targets higher, as suggested by the negative coefficients before $Market\,Sim.$ and $Embedding\,Sim.$ This result might shed light on the main motives of these acquisition transactions: bidders mostly seek to expand into new markets through these acquisition transactions, instead of reinforcing their positions in their existing markets.

1.7 Conclusion

I investigate the effects of information quality on value creation and revenue in failed-bank auctions by explicitly exploiting the specific auction mechanism. From the perspective of allocative efficiency of the failed banks' assets, the high marginal benefit of improving information quality found in the paper suggests the FDIC should a make policy effort to enhance information quality perhaps by extending due diligence periods and encouraging on-site visits, or by addressing the free-riding problem arising from mandatory information sharing among bidders, subject to the cost of the policy effort. Moreover, I find that information quality greatly complements participation in failed-bank auctions in generating higher value creation, in that additional bidders boost the winning valuation more if information quality is better.

By exploiting a policy change in 2010 that allows for flexibility in loss share percentage for targets over $500 million in book assets, I show that the flexibility largely increases the winning valuation in these auctions. Moreover, better information quality strongly complements the value effect of LSA flexibility, suggesting that joint policy effort on both LSA flexibility and information quality is necessary to exploit their complementarity in generating more efficient auction outcomes. The significant benefit of LSA flexibility also raises caution about recent discussion of the FDIC's phasing out of LSAs altogether, because servicing these agreements has high monitoring and administrative. The rapidly growing market for Representations and Warranties (R&W) insurance offered by private insurance companies for regular

M&A transactions may provide a substitute for LSAs that can preserve the benefit and help avoid the FDIC's servicing cost.

By quantifying the effects of the policy levers above on the expected winner's bid, I find evidence that the FDIC's focusing on monetary resolution cost under the Least Cost Resolution policy could result in suboptimal policy choices regarding information quality, participation, and LSA flexibility from the auction efficiency perspective. The FDIC tends to underinvest in improving information quality and offering LSA flexibility, because their benefits for auction revenue are much lower than those for value creation, and to overinvest in promoting participation because its benefit for auction revenue is much higher than that for value creation.

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Appendix

1.A A Sample Bid Summary and Data Cleaning Process

In this section, I use the bid summary of one failed-bank auction as an example to explain how I process the raw bid data and construct the sample used in the estimation.

Bidder	Type of Transaction	Deposit Premium %	Asset Premium $(000)	SF 1	SF 2	SF 3	Com 1	Com 2	Com 3
Winner: U.S. Bank, Minneapolis, MN	All deposit whole bank	0.00	(67,500)	N/A	N/A	N/A	N/A	N/A	N/A
Cover: Iberiabank, Lafayette, LA	All deposit whole bank with loss share	0.00	(8,799)	80%	80%	N/A	80%	80%	N/A
Other bid:	All deposit whole bank with loss share	0.00	(9,905)	80%	80%	N/A	80%	80%	N/A
Other bid:	All deposit whole bank with loss share	0.00	(29,820)	80%	80%	N/A	80%	80%	N/A
Other bid:	All deposit whole bank with loss share	0.00	(35,350)	80%	80%	80%	80%	80%	80%
Other bid:	All deposit whole bank with loss share	0.00	(44,900)	80%	80%	N/A	80%	80%	N/A
Other bid:	All deposit whole bank	0.00	(69,500)	N/A	N/A	N/A	N/A	N/A	N/A
Other bid:	All deposit whole bank	0.00	(72,813)	N/A	N/A	N/A	N/A	N/A	N/A
Other bid:	All deposit whole bank	0.00	(77,533)	N/A	N/A	N/A	N/A	N/A	N/A

Table 1.8: A Bid Summary

The table above is the bid summary table[20] for BankEast, Knoxville, TN, a bank closed on January 27, 2012. There are ten columns in the table. "Bidder" (column 1) reports the identity of the bidder who submits each of the bid, whenever such information is intended to be disclosed. In this example, the winner is U.S. Bank,

[20] The complete bid summary is available at https://www.fdic.gov/bank/individual/failed/bankeast-bid-summary.html

Minneapolis, MN, and the second place (cover) is Iberiabank, Lafayette, LA[21]. "Type of transaction" (column 2) describes the types of the listed bids. There are two types in this auction: "all deposit whole bank" and "all deposit whole bank with loss share". The difference between the two types is that the latter includes an LSA in the bid, while the former does not. "Deposit premium" (column 3) and "Asset premium" (column 4) are the two central components needed to compute the bid used in the final sample, which I describe in Section 3.2.3. "SF1" (column 5) to "SF3" (column 7) disclose the loss share percentage in three tranches of single-family mortgage loans. "Com 1" (column 8) to "Com 3" (column 10) reports the loss share percentage of commercial mortgage loans.

As described in Section 3.2.3, I then construct auction pools so that all bids within one pool are the same exact type, so they are comparable. In this example above, I identify the different pools by comparing the contents of all columns across bids. Two bids belong to the same auction pool if and only if the contents in all columns are the same except for the numbers in "Deposit premium" (column 3) and "Asset premium" (column 4). In this example, I can identify three auction pools. First, bid 1, 7, 8, 9 are in the pool with transaction type "all deposit whole bank". Second, bid 2, 3, 4, 6 are in the same pool with transaction type "all deposit whole bank with loss share", and the loss share is available for SF1, SF2, Com 1 and Com 2. Third, bid 5 is the only bid in the pool with transaction type "all deposit whole bank with loss share" where loss share percentage is 80% across all six tranches.

The first and second pool of this auction are kept in the final sample, and the third pool is discarded since there is only one bid in it.

Besides the bid summary table, the FDIC also discloses all bidders in the auction. In the same example, the following five banks are also in the auction: Bank of the Ozarks, Little Rock, AR, First State Bank, Union City, TN, First Tennessee Bank,

[21] The second place bid is the bid that will result in the lowest resolution cost after excluding all bids submitted by the winning bidder.

Memphis, TN, Great Southern Bank, Reeds Spring, MO, and Renasant Bank, Tupelo, MS. These participating banks are matched with their Call Reports data of the period leading up to the auction. The sample of all candidate bidders of all auctions is then used in the Full Information Maximum Likelihood Estimation in Section 1.6.4.

1.B Bank Network Embeddings

The bank network is an unweighted undirected graph in which every vertice (node) represents a bank, and every edge represents a competitive relationship. More specifically, I define two banks to be competitors if they both have branches in at least one same county. This graph is the only input for the network embedding algorithm. I denote the graph as $G = (V, E)$, where V is the set of vertices (banks), and E is the set of edges (competitive relationships). The goal of the representation learning algorithm is to find the mapping $f : V \rightarrow \mathbb{R}^d$ from the nodes to representation space of dimension d. The mapping f can also be regarded as a matrix of parameters of size $|V| \times d$. In addition, define $N(v) \subset V$ for all $v \in V$, as the neighborhood for any node v in the network. One simple definition of N is all the nodes connected to v. I will discuss the definition in this paper below. The algorithm then maximizes the following objective function, which is the log-probability of the observed network topology.

$$max_f \sum_{v \in V} logPr\left(N(v) | f(v) \right)$$

and the probability of any $n \in N(v)$ conditional on node v's representation is a soft-max function of the dot products of the representations of n and v,

$$Pr\left(n | f(v) \right) = \frac{exp\left(f(n) \cdot f(v) \right)}{\sum_{u \in V} exp\left(f(u) \cdot f(v) \right)}$$

Under some additional technical conditions that ensure computational tractability, the optimization problem can be solved using stochastic gradient ascent over the parameter space that defines mapping f.

I use the node2vec algorithm proposed by [22]. In this algorithm, the set of neighboring nodes $N(v)$ for any node v in the network is sampled using random walks from the source node v. Specifically, the sampler will take a step of length l in a random walk fashion from the source node v, and all nodes sampled in these l steps will be in the set $N(v)$. Intuitively, the nodes directly connected to the source node are most likely to be sampled, and the nodes not directly connected but still close to the source node are also likely to be sampled. So the resulting representations will feature high similarity among nodes directly connected, moderate similarity among nodes not directly connected but still close, and low similarity among nodes far away from each other.

1.C Bid Homogenization

As described in Section 1.5.2, the raw bids constructed from the bid summaries have to be homogenized before passing on to the structural estimation step. Specifically, the homogenized bids are constructed as follows

$$b_{kt} = \widetilde{b}_{kt} - Z_t \widehat{\eta},$$

where $\widetilde{b}_{kt}$ is the kth raw bid in auction t, and Z_t is a vector of target characteristics. $\widehat{\eta}$ is obtained through the following regression

$$\widetilde{b}_{kt} = \alpha(K_t) + Z_t \eta + e_{kt}$$

[22]The python and C++ implementation of this algorithm is available at https://snap.stanford.edu/node2vec/

The regression results are reported in the table below,

Variables	Bid
$2-bidder$	0.2366*
	(0.131)
$3-bidder$	0.2283*
	(0.131)
$4-bidder$	0.2384*
	(0.131)
$5-bidder$	0.2419*
	(0.131)
$6-bidder$	0.2513*
	(0.133)
Financial Vars	Yes
Transaction Vars	Yes
Loss Share Vars	Yes
Target Embedding	Yes
Year Dummies	Yes
Observations	882
$Adj.R^2$	0.84

Table 1.9: Bids Homogenization Regression

For exposition purposes, I only report the intercepts specific to auctions with a certain number of bidders. The final homogenized bids will then be constructed from the expression above. Or equivalently, the homogenized bids will be the residual from the regression above, plus the corresponding intercept. We can also see in the regression results that the average bids are mostly increasing in the number of bidders in the auction, which is consistent the prediction of a standard first price auction model where bidders tend to bid more aggressively when there are more bidders. Financial variables, Loss Share variables, Target Embedding are defined the same as in Table 1.2. Transaction variables include dummy variables for whole bank bids, insured deposit bids, bids with LSAs, and modified whole bank bids.

1.D Optimal Bid Functions

Given the objective function for a bidder specified in Section 1.5.1, the optimal bidding function $h(s;K)$ has to satisfy the following Ordinary Differential Equation,

$$h'(s;K) = [V(s,s) - h(s;K)] \frac{f_{\max s_j|s_i}(s|s)}{F_{\max s_j|s_i}(s|s)}$$

where s is the signal received by the bidder, K is the number of bidders in the auction, $V(s,y) = E[v_{kt}|s_{kt} = s, \max_{j\neq i} s_{jt} = y]$ is the expected valuation conditional on the signal received and winning the auction. $F_{\max s_j|s_i}(y|s) = Pr(\max_{j\neq i} s_{jt} < y|\, s_{it} = s)$ is the CDF of the maximum opponent's signal conditional on the bidder's own signal, and $f_{\max s_j|s_i}(y|s)$ is its PDF.

To pin down the bid function, we need to derive $V(s,y)$ and $F_{\max s_j|s_i}(y|s)$, given the parametric specification $v_{it} = c_t + a_{it}, s_{it} = v_{it} + e_{it}$ with $c_t \sim N(\mu, \sigma_c), a_{it} \sim N(0, \sigma_a), e_{it} \sim (0, \sigma_e)$ mutually independent.

First consider the joint probability $Pr(v_{it} < v, s_{it} = s, \max_{j\neq i} s_{jt} = s)$,

$$\begin{aligned}
& Pr\left(v_{it} < v, s_{it} = s, \max_{j\neq i} s_{jt} = s\right) \\
=& \int_{-\infty}^{\infty} Pr\left(a_{it} < v - c, a_{it} + e_{it} < s - c, \max_{j\neq i} s_{jt} = s \,\middle|\, c_t = c\right) \frac{1}{\sigma_c}\phi\left(\frac{c-\mu}{\sigma_c}\right) dc \\
=& \frac{K-1}{\sigma_c\sqrt{\sigma_a+\sigma_e}} \int_{-\infty}^{\infty} Pr\left(a_{it} < v - c, a_{it} + e_{it} < s - c |\, c_t = c\right) \\
& \Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2} \phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right) \phi\left(\frac{c-\mu}{\sigma_c}\right) dc \\
=& \frac{K-1}{\sigma_c\sigma_a\sigma_e\sqrt{\sigma_a+\sigma_e}} \int_{-\infty}^{\infty} \int_{s-v}^{\infty} \phi\left(\frac{s-c-e}{\sigma_a}\right) \phi\left(\frac{e}{\sigma_e}\right) de \\
& \Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2} \phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right) \phi\left(\frac{c-\mu}{\sigma_c}\right) dc
\end{aligned}$$

Similarly, we can get

$$
\begin{aligned}
& Pr\left(s_{it}=s,\max_{j\neq i} s_{jt}=s\right)\\
=&\int_{-\infty}^{\infty} Pr\left(a_{it}+e_{it}<s-c,\max_{j\neq i} s_{jt}=s\middle| c_t=c\right)\frac{1}{\sigma_c}\phi\left(\frac{c-\mu}{\sigma_c}\right)dc\\
=&\int_{-\infty}^{\infty}\frac{1}{\sqrt{\sigma_a+\sigma_e}}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)\frac{K-1}{\sqrt{\sigma_a+\sigma_e}}\Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\\
&\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)\frac{1}{\sigma_c}\phi\left(\frac{c-\mu}{\sigma_c}\right)dc\\
=&\frac{K-1}{\sigma_c\left(\sigma_a+\sigma_e\right)}\int_{-\infty}^{\infty}\Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{2}\phi\left(\frac{c-\mu}{\sigma_c}\right)dc
\end{aligned}
$$

Therefore, we can obtain

$$
\begin{aligned}
& Pr\left(v_{it}<v\middle| s_{it}=s,\max_{j\neq i} s_{jt}=s\right)\\
=&\frac{Pr\left(v_{it}<v,s_{it}=s,\max_{j\neq i} s_{jt}=s\right)}{Pr\left(s_{it}=s,\max_{j\neq i} s_{jt}=s\right)}\\
=&\frac{\sqrt{\sigma_a+\sigma_e}}{\sigma_a\sigma_e}\frac{\int_{-\infty}^{\infty}\int_{s-v}^{\infty}\phi\left(\frac{s-c-e}{\sigma_a}\right)\phi\left(\frac{e}{\sigma_e}\right)de\Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)\phi\left(\frac{c-\mu}{\sigma_c}\right)dc}{\int_{-\infty}^{\infty}\Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{2}\phi\left(\frac{c-\mu}{\sigma_c}\right)dc}
\end{aligned}
$$

The density function is then

$$
\begin{aligned}
& f_{v_{it}|s_{it},\max s_{jt}}\left(v|s,s\right)\\
=&\frac{d}{dv}\frac{Pr\left(v_{it}<v,s_{it}=s,\max_{j\neq i} s_{jt}=s\right)}{Pr\left(s_{it}=s,\max_{j\neq i} s_{jt}=s\right)}\\
=&\frac{\sqrt{\sigma_a+\sigma_e}}{\sigma_a\sigma_e}\frac{\int_{-\infty}^{\infty}\phi\left(\frac{v-c}{\sigma_a}\right)\phi\left(\frac{s-v}{\sigma_e}\right)\Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)\phi\left(\frac{c-\mu}{\sigma_c}\right)dc}{\int_{-\infty}^{\infty}\Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{2}\phi\left(\frac{c-\mu}{\sigma_c}\right)dc}
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
& V(s,s) \\
=& E\left[v_{kt} \middle| s_{kt}=s, \max_{j\neq i} s_{jt}=s \right] \\
=& \frac{\sqrt{\sigma_a+\sigma_e}}{\sigma_a\sigma_e} \frac{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} v\phi\left(\frac{v-c}{\sigma_a}\right)\phi\left(\frac{s-v}{\sigma_e}\right) dv \Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)\phi\left(\frac{c-\mu}{\sigma_c}\right) dc}{\int_{-\infty}^{\infty}\Phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)^2\phi\left(\frac{c-\mu}{\sigma_c}\right) dc} \\
=& \frac{\sigma_a}{\sigma_a+\sigma_e} s + \frac{\sigma_e}{\sigma_a+\sigma_e} \frac{\int_{-\infty}^{\infty} c\exp\left(-\frac{(c-\mu)^2}{2\sigma_c}-\frac{(s-c)^2}{\sigma_a+\sigma_e}\right)\mathrm{Erfc}\left(-\frac{s-c}{\sqrt{2(\sigma_a+\sigma_e)}}\right)^{K-2} dc}{\int_{-\infty}^{\infty}\exp\left(-\frac{(c-\mu)^2}{2\sigma_c}-\frac{(s-c)^2}{\sigma_a+\sigma_e}\right)\mathrm{Erfc}\left(-\frac{s-c}{\sqrt{2(\sigma_a+\sigma_e)}}\right)^{K-2} dc}
\end{aligned}
$$

where $\mathrm{Erfc}(\cdot)$ is the complementary error function.

Next, I derive $F_{\max s_j|s_i}(y\,|s) = Pr\left(\max_{j\neq i} s_{jt} < y\right| s_{it}=s)$.

$$
\begin{aligned}
& F_{\max s_j|s_i}(y\,|s) \\
=& \frac{Pr\left(\max_{j\neq i} s_{jt} < y, s_{it}=s\right)}{Pr\left(s_{it}=s\right)} \\
=& \frac{\int_{-\infty}^{\infty} Pr\left(a_{it}+e_{it}=s-c, \max s_{jt}<y \middle| c_t=c\right)\frac{1}{\sigma_c}\phi\left(\frac{c-\mu}{\sigma_c}\right) dc}{\frac{1}{\sqrt{\sigma_c+\sigma_a+\sigma_e}}\phi\left(\frac{s-\mu}{\sqrt{\sigma_c+\sigma_a+\sigma_e}}\right)} \\
=& \frac{\int_{-\infty}^{\infty}\frac{1}{\sqrt{\sigma_a+\sigma_e}}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)\Phi\left(\frac{y-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-1}\frac{1}{\sigma_c}\phi\left(\frac{c-\mu}{\sigma_c}\right) dc}{\frac{1}{\sqrt{\sigma_c+\sigma_a+\sigma_e}}\phi\left(\frac{s-\mu}{\sqrt{\sigma_c+\sigma_a+\sigma_e}}\right)}
\end{aligned}
$$

Hence, the density function is

$$
\begin{aligned}
& f_{\max s_j|s_i}(y\,|s) \\
=& \frac{d}{dy} F_{\max s_j|s_i}(y\,|s) \\
=& \frac{K-1}{\sigma_a+\sigma_e}\frac{\int_{-\infty}^{\infty}\Phi\left(\frac{y-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\phi\left(\frac{y-c}{\sqrt{\sigma_a+\sigma_e}}\right)^2\frac{1}{\sigma_c}\phi\left(\frac{c-\mu}{\sigma_c}\right) dc}{\frac{1}{\sqrt{\sigma_c+\sigma_a+\sigma_e}}\phi\left(\frac{s-\mu}{\sqrt{\sigma_c+\sigma_a+\sigma_e}}\right)}
\end{aligned}
$$

Then it is easy to get

$$
\begin{aligned}
&\frac{f_{\max s_j|s_i}\left(s\,|s\right)}{F_{\max s_j|s_i}\left(s\,|s\right)}\\
=&\frac{K-1}{\sqrt{\sigma_a+\sigma_e}}\frac{\int_{-\infty}^{\infty}\Phi\left(\frac{y-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-2}\phi\left(\frac{y-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{2}\phi\left(\frac{c-\mu}{\sigma_c}\right)dc}{\int_{-\infty}^{\infty}\Phi\left(\frac{y-c}{\sqrt{\sigma_a+\sigma_e}}\right)^{K-1}\phi\left(\frac{s-c}{\sqrt{\sigma_a+\sigma_e}}\right)\phi\left(\frac{c-\mu}{\sigma_c}\right)dc}\\
=&\sqrt{\frac{2}{\pi}}\frac{K-1}{\sqrt{\sigma_a+\sigma_e}}\frac{\int_{-\infty}^{\infty}\exp\left(-\frac{(c-\mu)^2}{2\sigma_c}-\frac{(s-c)^2}{\sigma_a+\sigma_e}\right)\mathrm{Erfc}\left(-\frac{s-c}{\sqrt{2(\sigma_a+\sigma_e)}}\right)^{K-2}dc}{\int_{-\infty}^{\infty}\exp\left(-\frac{(c-\mu)^2}{2\sigma_c}-\frac{(s-c)^2}{\sigma_a+\sigma_e}\right)\mathrm{Erfc}\left(-\frac{s-c}{\sqrt{2(\sigma_a+\sigma_e)}}\right)^{K-1}dc}
\end{aligned}
$$

Now we have every term in the ODE for the bid function, so the ODE can then be solved numerically.

1.E Simulated Methods of Moments Estimation Procedure

The procedure is described below,

- Given a set of parameters $(\mu, \sigma_c, \sigma_a, \sigma_e)$, I numerically solve the bid functions $h\left(s, K\right)$ that satisfy the following ordinary differential equation for all K, where K is the number of bidders in the auction, and s is the signal received by the bidder

$$h'\left(s;K\right)=\left[V\left(s,s\right)-h\left(s;K\right)\right]\frac{f_{\max s_j|s_i}\left(s\,|s\right)}{F_{\max s_j|s_i}\left(s\,|s\right)}$$

where $V\left(s,s\right)=E\left[v_{kt}\,|s_{kt}=s,\max_{j\neq i}s_{jt}=s\right]$ is the expected valuation conditional on the signal received and winning the auction. $F_{\max s_j|s_i}\left(s\,|s\right)=Pr\left(\max_{j\neq i}s_{jt}<s|\,s_{it}=s\right)$ is the CDF of the maximum opponent's signal conditional on the bidder's own signal, and $f_{\max s_j|s_i}\left(s\,|s\right)$ is its PDF. The detailed derivation is in Appendix 1.D

- Compute the rth model moments of bids for all K[23]

$$m_{rK}(\theta) = \frac{1}{\sqrt{\sigma_c + \sigma_a + \sigma_e}} \int_{-\infty}^{\infty} h(s; K)^r \, \phi\left(\frac{s}{\sqrt{\sigma_c + \sigma_a + \sigma_e}}\right) ds$$

where $\phi(\cdot)$ is the PDF for standard normal distribution.

- Let T_K be the observed number of auctions with K bidders, and T the total number of auctions, compute the model implied moments for the observed auctions $M(\theta) = (M_1(\theta), ..., M_R(\theta))$ with

$$M_r(\theta) = \frac{1}{T} \sum_K T_K m_{rK}$$

- Given the empirical moments $\widehat{M_r} = \frac{\sum_{t=1}^{T} \sum_{k=1}^{K_t} b_{kt}^r}{\sum_K T_K K}$, and denote $\widehat{M}$ as the vector containing $\widehat{M_r}$ for $r = 1, ..., R$, compute the score under some weighting matrix W,

$$J(\theta) = \left(\widehat{M} - M(\theta)\right)^T W \left(\widehat{M} - M(\theta)\right)$$

- Repeat the procedure above until $(\mu, \sigma_c, \sigma_a, \sigma_e)$ that minimizes the score $J(\theta)$ is found.

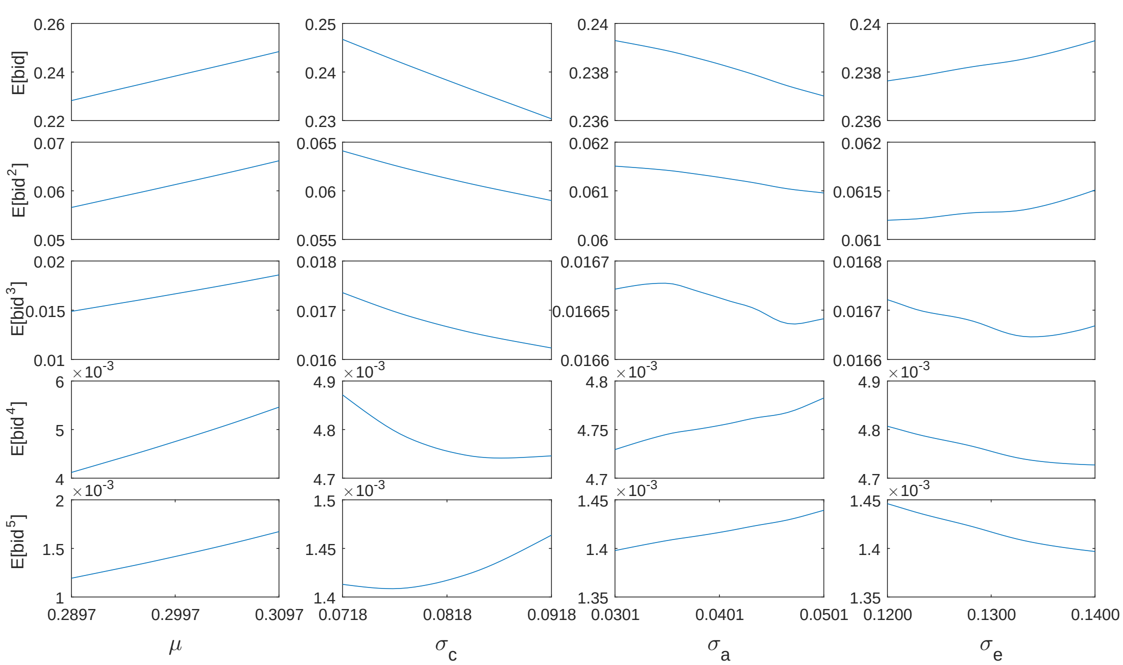
In practice, I set $R = 5$, so the algorithm will try to match the first five moments of observed bids. The estimate is obtained by a global optimization algorithm such as particle swarm or differential evolution.

I follow the literature using SMM approach in choosing the weighting matrix W, which is usually the inverse of the variance-covariance matrix of empirical moments. However, some special attention has to be paid when computing the variance-covariance matrix of the empirical moments in this context because bids within the same auction are not independent. I use the bootstrap method to compute the

[23] Typically, the model moments are computed using simulation in SMM estimation. In this paper, I use numerical integration since it is free of sampling error and computation time is similar.

variance-covariance matrix of the empirical moments of the bids. Specifically, I first construct a resample of the auctions with replacement from all observed auctions, then randomly take only one bid from each sampled auction. Then I compute the moments of bids based on the resample of bids. I repeat the process for $100,000$ times to obtain $100,000$ empirical moments of resamples. Then the variance-covariance matrix is simply the variance-covariance matrix of these resample moments. In this way, I guarantee that each auction will only provide one bid in computing the variance-covariance matrix of the moments.

In general, the exact data variations used to identify each parameter is hard to pin down in this type of nonlinear models. Hong and Shum (2002) show the four parameters do affect the bid functions in different ways, so the parameters are identifiable and estimable from a computational perspective. In the figure below, I show the comparative statics of the first five moments of the equilibrium bid distribution by varying the parameters around the estimated values. It is easy to see these parameters do have different impact on different bid moments.



1.F Expectation Maximization (EM) Estimation Procedure

The objective of this estimation procedure is to understand how do bidder characteristics affect their valuations towards a target failed bank. Ideally, one can simply regress the pseudo-values obtained through the structural estimation on various bidder characteristics. However, a practical obstacle here is that we cannot observe the bidder's identity for many bids. In fact, bids that can be matched with bidders are less than 1/8 of the sample, so a regression on the sample with matched bidders has a very low power to spot any statistical relationship.

The EM approach I use here makes use of not only the valuations that can be matched with bidders but also the characteristics of all participating bidders of all auctions. This estimation procedure is possible because the FDIC does disclose identities of all bidders in all auctions, even though the correspondence between bids and bidder identities are left out deliberately for all bidders except the top 2. The basic idea of this estimation procedure is to find the parameters that maximize the expected likelihood of observing all the valuations, given the characteristics of all participating bidders.

More concretely, I assume the valuations have the following form,

$$\widetilde{v}_{kt} = \widetilde{c}_t + \widetilde{X}_{kt}^{\top}\beta + \widetilde{u}_{kt}$$

where t indexes the target and k indexes the bid. $\widetilde{c}_t$ is the common component in the valuation for target t not related to the bidder characteristics. X_{kt} is a vector of characteristics of the bidder who submits bid k for target t. $\widetilde{u}_{kt}$ is the bidder-specific valuation not explained by bidder's characteristics. β is the coefficient of interest, which describes how bidders characteristics determine the valuation. Furthermore, I assume $\widetilde{u}_{kt}$ to be normally distributed with mean 0 and standard deviation σ_u. This parametric assumption gives closed forms for all the estimators in one step of this estimation procedure, which further makes the procedure computationally simple.

Valuations $\widetilde{v}_{kt}$ is not observable, so I replace valuation $\widetilde{v}_{kt}$ with signal $\widetilde{s}_{kt}$, which can be backed out with the structural estimates and observed bids,

$$\widetilde{s}_{kt} = \widetilde{c}_t + \widetilde{X}_{kt}^{\top}\beta + \widetilde{u}_{kt} + e_{kt}$$

e_{kt} is the noise embedded in bidders' signals, which is independent with $\widetilde{u}_{kt}$. The common component $\widetilde{c}_t$ is not observable. So we need to first demean both sides of the equation above for an auction t. Let $s_{kt} = \widetilde{s}_{kt} - \frac{1}{K_t}\sum_{k=1}^{K_t}\widetilde{s}_{kt}$ and $X_{kt} = \widetilde{X}_{kt} - \frac{1}{K_t}\sum_{k=1}^{K_t}\widetilde{X}_{kt}$, it is easy to get

$$s_{kt} = X_{kt}^{\top}\beta + \epsilon_{kt}$$

where $\epsilon_{kt} = \widetilde{u}_{kt} - \frac{1}{K_t}\sum_{k=1}^{K_t}\widetilde{u}_{kt} + e_{kt} - \frac{1}{K_t}\sum_{k=1}^{K_t} e_{kt}$. Notice that the variance of the residual term ϵ_{kt} is heteroskedastic given the following equation,

$$\begin{aligned} Var\left(\epsilon_{kt}\right) &= Var\left(\widetilde{u}_{kt} - \frac{1}{K_t}\sum_{k=1}^{K_t}\widetilde{u}_{kt} + e_{kt} - \frac{1}{K_t}\sum_{k=1}^{K_t} e_{kt}\right) \\ &= \left(\frac{K_t - 1}{K_t}\right)^2 \left(\sigma_u^2 + \sigma_e^2\right) \end{aligned}$$

where K_t is the number of bidders in auction t. Therefore, we know $\epsilon_{kt} \sim N\left(0, \left(\frac{K_t-1}{K_t}\right)^2\left(\sigma_u^2 + \sigma_e^2\right)\right)$. That is, the variance of ϵ_{kt} depends on the number of bidder in that auction. For simplicity, let $\sigma = \sqrt{\sigma_u^2 + \sigma_e^2}$, so the model is characterized by parameters β and σ.

Ideally, $\theta = (\beta, \sigma)$ can be estimated via maximum likelihood estimation,

$$\widehat{\theta}_{MLE} = argmax_{\theta} \sum_{t=1}^{T} \sum_{k=1}^{K_t} \log f_{e_t} \left(s_{kt} - X_{kt}^{\top} b; \theta \right)$$

However, the MLE above is not directly feasible because, for some valuations v_{kt}, X_{kt} is not obtainable since we do not observe the identity of the bidder. In fact, X_{kt} cannot be calculated even for observable bidders as long as at there exists any unobservable bidder in that auction, since the mean characteristics $\frac{1}{K_t} \sum_{k=1}^{K_t} \widetilde{X}_{kt}$ depend on all bidders in the auction.

Denote the set of all bidders characteristics for target t by $\widetilde{\mathscr{X}_t} = \left\{ \widetilde{X}_{1t}, ..., \widetilde{X}_{N_t t} \right\}$, where N_t is the total number of bidders for target t. N_t is different from K_t since K_t is the number of bids for target t. N_t can be greater than K_t if there are multiple auctions for different pools of the same failed bank because not all bidders participate in all pools. Given $\left\{ \widetilde{\mathscr{X}_t} \right\}_{t=1}^{T}$, θ can be estimated by maximizing the expected log-likelihood

$$\widehat{\theta}_{EM} = argmax_b E_{X|\widetilde{\mathscr{X}}} \left[\sum_{t=1}^{T} \sum_{k=1}^{K_t} \log f_{\epsilon_t} \left(s_{kt} - X_{kt}^{\top} b \right) \middle| \left\{ \widetilde{\mathscr{X}_t} \right\}_{t=1}^{T}, \theta \right]$$

The estimation procedure starts with an initial guess of $\theta_{old} = (\beta_{old}, \sigma_{old})$. Then one can compute the joint conditional probability $Pr \left(\{X_{kt}\}_{k=1}^{K_t} \middle| \{v_{kt}\}_{k=1}^{K_t}, \widetilde{\mathscr{X}_t}, \theta_{old} \right)$.

Given $\widetilde{\mathscr{X}_t}$, the possible configurations of the tuple $\{X_{kt}\}_{k=1}^{K_t}$ are finite. To illustrate this, let K_{1t} be the number of bids where bidder identities are observable, and K_{2t} be the number of bids where bidder identities are unobservable. Then $\{X_{kt}\}_{k=1}^{K_t}$ only has P_t configurations, where

$$P_t = \frac{N_t!}{(N_t - K_{2t})!}.$$

Intuitively, P_t is all possible K_{2t} permutations out of N_t elements. In other words, there are P_t different possible combinations of bidders who submit the K_{2t} bids with unobservable bidders. Denote $\{X_{kpt}\}_{k=1}^{K_t}$ as the pth permutation of demeaned bidder characteristics, where

$$X_{kpt} = \begin{cases} \widetilde{X}_{kt} - \frac{1}{K_{1t}} \sum_{k \in K_{1t}} \widetilde{X}_{kt} - \frac{1}{K_{2t}} \sum_{k \in K_{2t}} \widetilde{X}_{kpt} & ; k \in K_{1t} \\ \widetilde{X}_{kpt} - -\frac{1}{K_{1t}} \sum_{k \in K_{1t}} \widetilde{X}_{kt} - \frac{1}{K_{2t}} \sum_{k \in K_{2t}} \widetilde{X}_{kpt} & ; k \in K_{2t} \end{cases}$$

Now we can further get

$$Pr\left(\{X_{kpt}\}_{k=1}^{K_t} \middle| \{s_{kt}\}_{k=1}^{K_t}, \widetilde{\mathscr{X}_t}, \theta \right) = \frac{\prod_{k=1}^{K_t} \exp\left(-\frac{\left(s_{kt} - X_{kpt}^{\top}\beta\right)^2}{2\left(\frac{K_t - 1}{K_t}\right)^2 \sigma^2} \right)}{\sum_{p=1}^{P_t} \prod_{k=1}^{K_t} \exp\left(-\frac{\left(s_{kt} - X_{kpt}^{\top}\beta\right)^2}{2\left(\frac{K_t - 1}{K_t}\right)^2 \sigma^2} \right)}$$

For expositional simplicity, I define the conditional probability as $w_{pt}(\theta)$, $\{v_{kt}\}_{k=1}^{K_t}, \widetilde{\mathscr{X}_t}$ are left out since they are taken from the sample which does not change throughout the estimation procedure. Notice that if all bids are matched to bidders, there is only one possible permutation $P_t = 1$.

Next, we can update the estimate of θ by maximizing the expected log-likelihood conditional on $w_{pt}(\theta_{old})$ and the sample.

$$\theta_{new} = argmax_{\theta} \sum_{t=1}^{T} \sum_{k=1}^{K_t} \sum_{p=1}^{P_t} w_{pt}(\theta_{old}) \log f_{\epsilon_t}\left(s_{kt} - X_{kpt}^{\top} b; \theta\right)$$

Given the normality of ϵ, the estimator θ_{new} can be obtained in closed form,

$$\beta_{new} = \left(\sum_{t=1}^{T} \sum_{k=1}^{K_t} \sum_{p=1}^{P_t} w_{pt}(\theta_{old}) X_{kpt} X_{kpt}^{\top} \right)^{-1} \sum_{t=1}^{T} \sum_{k=1}^{K_t} \sum_{p=1}^{P_t} w_{pt}(\theta_{old}) s_{kt} X_{kpt}$$

$$\sigma_{new}^2 = \frac{\sum_{t=1}^{T} \sum_{k=1}^{K_t} \sum_{p=1}^{P_t} w_{pt}(\theta_{old}) \frac{K_t^2}{(K_t - 1)^2} \left(s_{kt} - X_{kpt}^{\top} \beta_{old}\right)^2}{\sum_{t=1}^{T} K_t}$$

Then one can check for convergence by computing the change from θ_{old} to θ_{new}. If the stopping criterion is not satisfied, one can let $\theta_{old} = \theta_{new}$ and repeat the process above until the stopping criterion is met.

The standard errors of the final estimate θ_{EM} can be obtained in closed form by computing the Hessian matrix of the expected log-likelihood with respect to θ at the estimate θ_{EM} following Jamshidian and Jennrich (2000). It is easy to get the estimate of the Hessian matrix $\hat{H}(\theta_{EM})$

$$-\frac{1}{\sigma_{EM}^2}\sum_{t=1}^{T}\sum_{k=1}^{K_t}\sum_{p=1}^{P_t}\frac{K_t^2}{(K_t-1)^2}w_{pt}(\theta_{EM})\begin{pmatrix} X_{kpt}X_{kpt}^\top & \frac{2}{\sigma_{EM}}X_{kpt}\left(s_{kt}-X_{kpt}^\top\beta_{EM}\right) \\ \frac{2}{\sigma_{EM}}X_{kpt}\left(s_{kt}-X_{kpt}^\top\beta_{EM}\right) & \frac{3\left(s_{kt}-X_{kpt}^\top\beta_{EM}\right)^2}{\left(\frac{K_t-1}{K_t}\right)^2\sigma_{EM}^2}-\frac{K_t-1}{K_t} \end{pmatrix}$$

Therefore, the variance-covariance matrix of the estimate θ_{EM} is the following, and the standard errors of each of the estimate can be then obtained accordingly.

$$\widehat{Var}(\theta_{EM}) = -\widehat{H}(\theta_{EM})^{-1}.$$

1.G Variable Definitions

The following table summarizes the variable definitions and data sources used to construct these variables.

Variable	Definition	Source
Bid	$\frac{A+\Delta A-D(1+\Delta D)}{A}$,where A is the book assets of the auction target, D is the book value of the target's deposits, ΔA is the asset premium of the bid in dollar amount, ΔD is the deposit premium in percentage	FDIC bid summary
Equity Ratio	Book value of equity divided by book value of assets of the bank in the last available Call Reports before the corresponding transaction	Call Reports

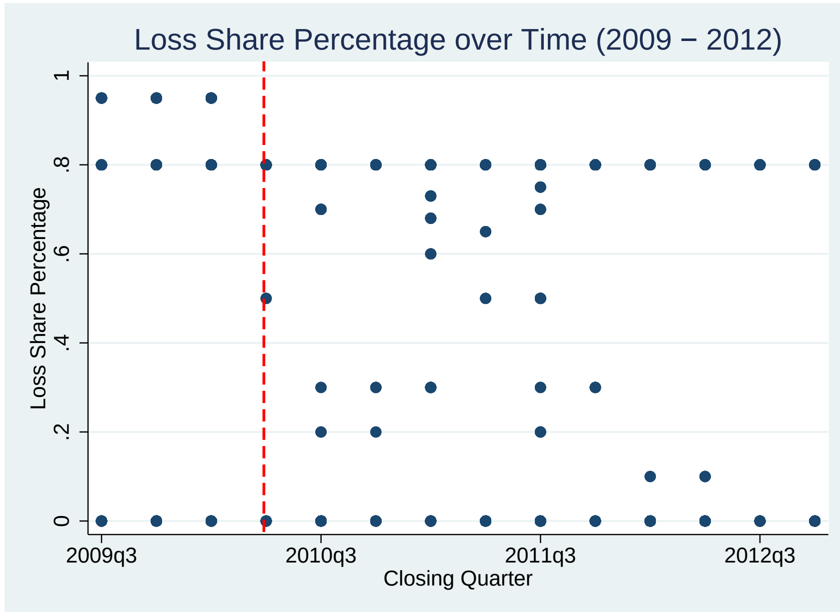
Variable	Definition	Source
Loan Ratio	Book value of total loans divided by book value of assets in the last available Call Reports before the corresponding transaction	Call Reports
%Residential	Book value of all residential real estate loans divided by book value of loans in the last available Call Reports before the corresponding transaction	Call Reports
%C&I	Book value of all commercial and industrial loans divided by book value of loans in the last available Call Reports before the corresponding transaction	Call Reports
OREO Ratio	Book value of other real estate owned divided by book value of assets in the last available Call Reports before the corresponding transaction	Call Reports
Loan Earn	Total income earned but now collected on loans divided by book value of assets in the last available Call Reports before the corresponding transaction	Call Reports
NPL Ratio	Book value of nonperforming loans divided by book value of assets in the last available Call Reports before the corresponding transaction. Nonperforming loans include all loans over 30 days past dues, and nonaccrual loans.	Call Reports

Variable	Definition	Source
ROA	Net income after tax divided by book value of assets in the last available Call Reports before the corresponding transaction	Call Reports
Liquidity Ratio	Net federal funds purchased divided by book value of assets in the last available Call Reports before the corresponding transaction	Call Reports
Size	Natural log of book value of assets in millions in the last available Call Reports before the corresponding transaction	Call Reports
Age	Natural log of number of years since chartered before the corresponding transaction	Call Reports
ΔHHI	The average change in Herfindahl–Hirschman Index, calculated using deposit shares, in all the counties the bidder will be in, if the bidder absorbed all deposit of the target bank.	Summary of Deposits
Loan Sim.	Cosine similarity of the bidder's and target's loan portfolio. A bank's portfolio is a vector of length 3 consisting of the fractions of residential loans, C&I loans, and consumer loans relative to the banks entire loan portfolio.	Call Reports
Distance	The simple average of all pairwise distance between all bidder's branches and all target's branches in hundreds of kilometers.	Summary of Deposits

Variable	Definition	Source
Market Sim.	Cosine similarity between the bidder's and the target's market indicator vectors. Each entry of a bank's market indicator vector is an indicator variable equal to 1 if the bank is in that corresponding county.	Summary of Deposits
Embedding Sim.	Cosine similarity between the bidder's and target's embedding vectors. Embedding vectors are 16-dimensional vectors obtained using network embedding technique on the graph representing the geographical competitive relationship among all banks.	Summary of Deposits
Receivership Duration	Number of months between the Call Reports date on which the equity ratio of the failed bank falls below 2% and the closing date.	Call Reports

1.H Loss Share Percentages around Q2, 2010

Starting from 2010 Q2, the FDIC allows bidders in auctions for targets over $500 million in book assets to choose the loss share percentage. The following graph plots the loss share percentages of all bids in the sample around 2010 Q2, where we can see a lot of nonstandard loss share percentages are chosen after the flexibility is introduced.



Loss Share Percentage over Time (2009 − 2012)
Loss Share Percentage
0
.2
.4
.6
.8
1
2009q3
2010q3
2011q3
2012q3
Closing Quarter

Chapter 2

The Competitive Spillover Effect of Bank Failure

2.1 Introduction

Researchers and policymakers usually consider bank failures to have a more substantial negative impact on the rest of the economy than failures of other types of firms, because of banks' systemic importance. Banks are crucial to many other parties in the economy. For example, closure of a bank will very likely lead to loss of banking services for its depositors and borrowers, which can hinder various aspects of economic activities. Observers have also argued that banks are more inter-connected than firms in a typical industry. One bank failure can easily generate a spillover effect on other banks in this tightly connected system. The spillover effect can even influence the entire economy given banks' systemic role. Thus, policymakers and regulators pay special attention to the resolution of failed banks.

The Federal Deposit Insurance Corporation (FDIC) is the agency responsible for resolving failed banks. In the most recent financial crisis alone, FDIC has resolved over 500 banks, with over $600 billion in book assets involved. The objective of the

FDIC when resolving these banks is to minimize the cost to its Deposit Insurance Fund (DIF)[1]. To do so, the FDIC typically finds another healthy bank to acquire a failed bank via an auction mechanism. The acquirer shares the resolution cost that otherwise the FDIC would bear entirely via direct payout covering the insured deposits. These acquisition transactions facilitated by the FDIC can dramatically change the industrial organization structure of the banking sector, shaping the way each bank failure impacts the rest of the sector.

Previous literature related to the spillover effect of bank failure has mainly focused on information-based channels (Schumacher (2000), Aharony and Swary (1983), Aharony and Swary (1996) among others): one failed bank reveals adverse information regarding other banks that share some of the failed entity's characteristics. The role played by the FDIC in determining the impact of bank failures has largely been overlooked, yet it has a significant influence on the competitive landscape of the whole banking system through its choices about the resolution of failed banks. Here, I explore a novel industrial-organization based channel of bank failure spillover effect that is tightly related to the FDIC's resolution policy.

Estimating a peer effect model that captures the inter-dependency of bank failures by exploiting the partially overlapping branch networks among banks, I show that on average bank failures lead to lower failure probability for affected banks competing with the failed bank. The effect is economically strong: a bank with one failed competitor has ten times lower probability of failure than an otherwise identical bank with no failed competitor, even with other financial and economic factors controlled. Consistent with the lower failure probability, banks with more failed competitors have better accounting performance on average. Moreover, I show the magnitude and the direction of the spillover effects depend crucially on the competitive relationship among three parties: a failed bank, the acquirer of the failed bank, and other affected

[1] This is called lowest cost resolution policy, which came into effect in 1994 following the FDIC Improvement Act (FDICIA)

banks competing with the failed bank. Affected banks competing with the acquirer experience a larger drop in failure probability than those not competing with the acquirer. I also show that the former group of banks tightens its supply of mortgage loans more than the latter group. I interpret the results as evidence of a competition channel of the bank failure spillover effect: affected banks that are competitors of the acquirer see a consolidation of banks in their markets, and thus a gain in market power, leading to better performance, and lower failure probability. These results suggest that the implications of resolution options for the industrial organization structure among affected banks have to be carefully examined to avoid hidden spillover costs.

To reach these inferences, I overcame a series of technical and empirical challenges. Identification of interdependency among a group of individuals is typically impossible due to Manski's reflection problem, in which the failure of all banks is determined simultaneously in equilibrium. I took advantage of the partially overlapping branch networks of banks to construct intransitive peer groups that can help with the identification. The basic idea is that the spillover effect on one bank from its competitor can be identified by instrumenting the competitor's status with the status of the competitor's competitor. I also employed an unsupervised machine-learning technique known as the Gaussian Mixture Model (GMM) to cluster bank failures that may affect each other. To control for high-dimensional fixed effects in a sample of moderate size, I made use of some state-of-the-art dimension reduction techniques, including the Autoencoder.

The findings in this paper have implementable policy implications for the resolution of failed banks, especially during times of financial crisis when financial stability is needed the most. The existence of a competitive channel of the spillover effect suggests that the FDIC should favor acquirers that are competing with most of the failed bank's competitors. These acquirers will benefit the banks affected by the failed competitor with a lower failure probability on average, preventing cascading failures in the market. This paper contributes to the literature in at least the following three ways. First, to the best of my knowledge, this is the first paper that quantifies the spillover effect of bank failures in the entire banking system through the branch networks. Second, this paper provides evidence for a novel industrial-organization-based mechanism for transmission of the bank failure spillover effect, via the competitive relationship among banks following changes in the industrial-organization structure resulting from the resolution of bank failures. Third, the method used in this paper can be utilized to analyze other interdependencies among banks to better understand the systemic roles that banks play.

The rest of the paper is organized as follows. I discuss aspects of the institutional backgrounds and related literature in the remainder of this section. Section 3.2 introduces the data and the empirical methodology used in this research. Section 2.3 links the policy background and my research questions to develop some intuition and hypotheses about the direction, as well as the economic mechanism of bank failure spillover effect. Section 3.3 presents and discusses the results. Section 3.4 concludes.

2.1.1 Bank Failure Resolution: Process and Policy

Whenever an FDIC-insured bank is about to go bankrupt, its charter authority requests that the FDIC put it into receivership. The first option the FDIC can take to resolve this failed bank is to liquidate the bank's assets and then repay all insured deposits. If the liquidation value is not enough to cover all insured deposits, the FDIC will have to pay out of the DIF[2]. In most bank failure cases, the FDIC does not prefer the liquidation option because it is not cost efficient from the agency's perspective. In the end, bank customers and taxpayers bear the entire cost of failure resolutions. Therefore, it is FDIC's responsibility and objective to find the least costly resolution option .

[2]The insured amount is capped at $250,000 for each account at each insured bank by FDIC as of 2018.

In practice, the FDIC almost always seeks acquirers for a failed bank to share the cost of resolution. Resolution through acquisition decreases the monetary payout from the insurance fund. Another very important advantage of resolution through acquisition over resolution through liquidation is that the operation of the failed bank will not be interrupted. To a community with limited access to banking services, such an interruption may be devastating. For example, local businesses may not be able to obtain timely financing. Depositors may not be able to withdraw cash for a period of time, creating liquidity problems, even though their insured deposits covered by FDIC will be repaid eventually.

Typically, the FDIC first goes to the failed bank and gathers essential information about it, and then shares the information with eligible potential acquirers, which are usually healthy financial institutions. The FDIC also uses the information gathered to estimate the cost of the liquidation option, which can be thought of as the last resort for resolving the failed bank. Then the FDIC organizes an auction for the failed bank, using a first-price sealed-bid format. Eligible bidders have the option to do due diligence, and collect information by sending their own personnel to the failed bank, before submitting their bids. Upon receiving all the bids, the FDIC will choose the winner. Then, usually over a weekend, the entire failed bank[3] is transferred over to the acquirer, and all operations continue as usual under a different brand on the next business day. Banking services to the communities served by the failed bank are never interrupted. The FDIC pays out or is paid according to the terms of the winning bid. More specifically, if the winning bidder says it will be willing to assume the entire failed bank for $100 million, then the FDIC will pay $100 million to the winner. On the contrary, if the winning bidder says it is willing to pay $100 million to take over the bank, then the winner will pay the FDIC $100 million.

[3]The exact pool of assets transferred to the acquirer is dependent on the specific bid. For example, if the winning bid does not include some mortgage loans, then FDIC will have to retain these mortgage loans and then liquidate over time after the auction.

In a typical failed-bank auction with multiple bidders, the FDIC needs to choose between resolution through liquidation or through acquisition. If acquisition is preferred, the agency then chooses the winning bidder, or the acquirer. When choosing among resolution alternatives, the FDIC is bound by the **Least Cost Resolution Policy**, which imposes two crucial requirements on its resolution choices. First, FDIC can only consider monetary cost; it cannot factor in less tangible cost, such as welfare cost, into the cost evaluation. Second, the agency has to choose the option that is the least costly to itself, or equivalently, to the DIF. Anti-corruption and conflict of interest concerns may justify this requirement. The current least cost resolution policy is a result of FDICIA passed in 1991[4]. In this paper, I find this policy has important implications for the bank failure spillover effect due to its impact on the competitive landscape through the resolution process.

2.1.2 Related Literature

This paper is broadly related to the literature studying the interdependency of banks within the entire national banking network. The objective of research on interdependency is typically to understand how adverse shocks to one or a subset of banks are transmitted to other banks, and that transmission is usually referred to as contagion. A large body of literature investigates so-called information-based contagion, in which the failure of one bank transmits adverse signals about other banks with which the failed bank shares some characteristics. These adverse signals may have a negative impact on the similar banks. Various empirical research yields evidence of such information-based contagion. In particular, Schumacher (2000) studies the Mexican devaluation in 1994 as a shock to Argentina's banking system and looks at effects on different types of banks. Only a subset of banks more exposed to the currency

[4]Prior to the passage of FDICIA, FDIC has quite some discretion when it comes to choosing among acquirers. FDIC can choose any bidder as the acquirer, as long as the cost associated with that bidder is less than the liquidation alternative.

shock experienced bank runs, providing evidence consistent with information-based contagion. Aharony and Swary (1983), Aharony and Swary (1996), and others look at the capital market reaction to big bank failures. The authors find the magnitude of the adverse impact on abnormal returns is negatively correlated with distance from the failed banks. Using distance as a similarity proxy between banks, the authors argue the evidence is consistent with information-based contagion. More recently, Furfine (2003) and Muller (2006) provide evidence that inter-bank markets can be a channel of bank contagion using US and Swiss bank data respectively.

With a similar objective but a different industry setting, Bernstein et al. (2017) investigates the spillover effects of the bankruptcy of manufacturing establishments. Specifically, the authors look at how liquidation and reorganization differently impact a local economy. Using the random assignments of bankruptcy judges as the exogenous variation in the resolution methods of bankruptcy. They find that liquidation of failed establishments leads to more severe adverse effects on local proximate firms than reorganization.

This paper is closely related to the literature studying the resolution of failed banks. Kang et al. (2015) estimates a dynamic choice model of FDIC closing decisions of failed banks. Concretely, they estimate two types of costs to the FDIC associated with closing a bank: monetary cost and non-monetary cost. Monetary cost is the amount directly paid from the DIF, whereas non-monetary cost is other cost that also enters into the FDIC's decision on the timing of closing failed banks. Although the FDICIA requires the agency to consider only monetary cost when making resolution decisions, Kang et al. (2015) provides evidence that non-monetary cost remains a consideration in decisions on the timing of closure. The distinction between non-monetary cost as defined in Kang et al. (2015) and the spillover cost I attempt to identify in this paper is that the former affects the optimality of the timing of closure, whereas the latter affects the optimality of resolution choices, given the closure or resolution process has already started.

The most recent work on the resolution of failed banks is Granja et al. (2017). The authors look directly into auctions for failed banks, which are the predominant form of resolution. They find that, compared with other bidders, the winners of these auctions tend to be better capitalized and also tend to be geographically closer to the failed banks and to have assets more similar to the failed banks'. They rationalize these findings using an auction model with budget constraints and argue that a substantial misallocation of failed banks' assets exists, which leads to large efficiency loss. My paper complements their research by pointing out another cost, one due to a spillover effect of bank failures that is unaccounted for under the FDIC's least cost resolution policy.

Methodologically, this paper is related to the literature on identification of peer effects among interacting individuals within some groups. Manski (1993) first points out the challenge to identifying such peer effects presented by the so-called reflection problem, whereby the behavior of each individual is endogenously determined, if all individuals can affect and be affected by all others within a group. He also provides some settings in which such peer effects can be identified. One setting that has been explored and exploited extensively is that of intransitive, or partially overlapping peer groups. I discuss in more detail how peer effects can be identified in such a setting in Section 3.2.2. Notably, Bramoullé et al. (2009) and De Giorgi et al. (2010) prove how intransitive peer groups can help a researcher identify peer effects among interacting individuals. They also provide more methods to deal with some related challenges frequently seen in peer effect studies. One notable application of such methods is Lewellen (2013), in which the author identifies how the compensation of top executives is benchmarked against their competitors' compensations.

2.2 Empirical Strategy

2.2.1 Data

The data used in this paper consist of four primary sources, all of which are available on the FDIC's website. The FDIC maintains a list of historical bank failures. For all bank failures from October 2000 to June 2017, I gathered the identity of the failed banks and their official closing dates, and scraped all available bidding information on these bank failures from the FDIC website. The disclosure of the bidding information was made following Freedom of Information Act requests in November 2009. The "Bid Summary" contained in the disclosure of each bank failure case has the following information: the name and bid amount of the winner, the name and bid amount of the second-highest bidder, and the names of all other losing bidders and losing bid amounts. It is worth noting that the correspondence between losing bidders and their bids is deliberately left out. In other words, for all but the top two least costly bids, the identity of the bidder is obscured.

The Summary of Deposits (SOD) is also available from the FDIC, providing annual reports of the deposits of all branches of all FDIC-insured banks. More importantly, using the geographical location of the branches available in this data set, I was able to identify competitive relationships between banks based on whether or not they operated in the same geographical region, which was the base for constructing peer groups in this research.

Call Reports data contain the quarterly financial statements of banks. From this data set I constructed various performance measures, loan portfolio characteristics, and so on.

In addition to the bank data obtained from the FDIC's website. I also make use of Home Mortgage Disclosure Act (HMDA) data to explore the impact of bank failures on mortgage lending activities.

2.2.2 Identification Strategy

The first main objective of this study is to identify the spillover effect of one failed bank on their competing banks' failure probability. Below, I give the baseline model describing the interdependency of bank failures, and then explain the challenges met and methods used to identify the spillover effect.

$$F_{it} = \alpha + \beta \sum_{j \in P_i} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it} \tag{2.1}$$

F_{it} is an indicator variable equal to 1 if bank i failed at period t. P_i is the set of banks competing with bank i. The competing relationship between banks is defined in details later. X is a vector of exogenous variables affecting bank failures. M_{it} is the set of markets bank i is in at period t. μ_{mt} is the impact of market m at period t on the failure of all banks operating in that market at that period.

Identification of this model is typically challenging, if feasible at all, because of the simultaneity problem, whereby competing banks affect each other on their failure. To be specific, the failure of a group of banks will be determined jointly given all structural equations as in 2.1 for every bank. This is referred to as Manski's reflection problem (Manski, 1993) in many areas of social science studies in which researchers try to identify how one individual's behavior is affected by interacting with other individuals in the same social group.

β is usually called the *endogenous effect*, which is also the main coefficient of interest. I also refer to this effect as the spillover effects of bank failures. This effect is endogenous because the failure of each bank is determined jointly given this model. γ is the *exogenous effect* since it is capturing the impact of competitors characteristics on the failure of one bank. μ's are the *correlated effect* in this case, which captures the fact that a group of banks may fail at the same time because they are subject to similar economic conditions from similar markets.

The endogenous peer effect β has important implications for policies regarding failed bank resolutions. First of all, this effect might be a benefit or cost that current least-cost resolution policy does not take into account. Moreover, if β varies with certain characteristics of the parties and situations related to a bank failure, it may provide insights on how to improve on current resolution policy to achieve more efficient resolutions by avoiding unfavorable spillover effects. This coefficient is also crucial from the perspective of economic theories: it can shed light on the economic mechanism that transmits the impact of bank failures throughout the entire banking system.

This model, as described in equation 2.1, is adapted from a typical peer effect model, a linear-in-means model. The outcome variable of one individual in the group, in this case, F_{it}, is a linear function of mean failure rate, and mean characteristics of the individual's peers. For interpretation purposes, I use the total number of peer failures on the right hand side, instead of mean peer failure rate. In this setup, the coefficient β represents the impact of one bank failure on the average failure rate of all its peers. A more formal demonstration can be found in Appendix 2.A.

Two central ingredients in this study help identify this spillover effect. The first one is the inclusion of correlated effect μ's. Without the correlated effect, the impact on bank failures from local economic shocks will be falsely attributed to the endogenous effect β or the exogenous effect γ. The correlated effect is particularly relevant in the context of bank failure since clustered bank failures usually only occur under severe adverse economic shocks. For example, the vast majority of bank failures that happened during the last two decades were during 2007 and 2008 as a consequence of the financial crisis. In practice, I include indicator variables for all MSA$\times$Year. That is, if bank i is in MSA 35620[5] in the year 2011, then the indicator of bank i for MSA 35620 of the year 2011 will be 1. One technical assumption is needed for

[5]New York - New Jersey - Pennsylvania Metropolitan Statistical Area.

identification: for any given year, the bank composition of any MSA cannot be the combination of any other MSA's. This guarantees that the matrix with each row being the indicator vector of whether one bank is present in all MSAs has full column rank. This assumption is indeed satisfied in the data because in any MSA, there are banks only operating in that one MSA.

The second crucial ingredient for identification is the partially overlapping branch networks of banks. As pointed out in Manski (1993), the spillover effect β cannot be identified if every individual in a social group is affected by all other individuals in the same group. However, De Giorgi et al. (2010) shows that the effect can be identified with partially overlapping peer groups, sometimes called intransitive peer groups. In this paper, I define the peer group of any bank i to be all banks that are operating in any MSA where bank i also operates. On the flip side, two banks are not peers if there is no MSA in which both operate. This definition of peer groups makes peer groups intransitive: the fact that Bank A and Bank C are both peers of Bank B does not imply Bank A and C are peers. With intransitive peer groups, identification is obtained through effectively instrumenting failures among the focal bank's peers using the failures among banks that are peers to the focal bank's peers.. Here, I use a three-bank example to demonstrate how identification is achieved with an intransitive peer group. In the example, it is hard to identify the spillover effect of Bank B on Bank A because of the reflection problem: Bank A is affecting Bank B's failure at the same time. However, here we have a third bank Bank C, which is also a peer (The terms "peer" and "competitor" are used interchangeably in this paper) of Bank B, but not of Bank A. Hence, Bank C's status, i.e., failure or no failure, is a valid instrument for Bank B's status, in efforts to identify the spillover effect of Bank B on Bank A. We can check the two conditions for a valid instrument here. First of all, Bank C's status is obviously correlated with Bank B's status since they are peers, so Bank C's status satisfies the *relevance* condition as an instrument for that of Bank B. Second, Bank C's status will only affect Bank A's status through Bank B, since Bank A and Bank C are not directly competing. Hence, Bank C's status also satisfies the *exclusion restriction* as an instrument. Therefore, Bank C's status is a valid instrument with which to identify Bank B's spillover effect on Bank A.

2.2.3 Failure Epochs

Given the model specified in (2.1), the probability of failure of each bank in the economy is jointly determined by exogenous bank characteristics, economic conditions, and the competitive relationships among banks. The first step of mapping data onto the model is to properly define periods t's. This is important because the model is implicitly assuming failures happening in period $t+1$ cannot be directly affected by failures that happened in period t. In the data, I can only observe the official closure date on which a failed bank ceased to operate as an entity. Since resolution processes vary in time for different failed banks, we may see that simultaneous bank failures, or bank failures that are dependent through the spillover effect, have very different official closure dates.

I argue that each period t has to be a window of dates of appropriate length. If a period is too short, I would be assuming away potential inter-dependency among some bank failures. If a period is too long, the impossible phenomenon of future events affecting past events appears. For example, if a period covers ten years, then I am essentially allowing banks closed in 2013 to cause the failures of banks closed in 2004. I argue the appropriate length of a period is around one year. According to the Handbook of Resolution from the FDIC, the total length of a resolution process can be anywhere from several months to over a year. So failures that happen on the same date can have closure dates around one year apart.

A simple definition of periods is that t is a specific calendar year. That is, the model allows for interdependency of failures of different banks that happen during the same calendar year. However, an apparently odd implication of this definition is that the failure of a bank closed on January 1, 2009, has nothing to do with the failure of a bank closed on December 31, 2008. This definition may assume away potential spillover effects among failures close to each other but in different calendar years.

This paper adopts a more data-driven approach to define time periods. In particular, I assume bank failures in the sample period occurred in several epochs. Within each epoch, bank failures are jointly determined, whereas failures happening in different epochs are not directly interdependent. Each failure is assumed to be in only one epoch, and the different observable failure are generated from some distribution around the central date of that epoch. The challenge here is that we cannot observe epochs associated with each failure. Hence, the task is to infer which epoch each failure belongs to using only the observed failure dates. In the language of Machine Learning, the problem of inferring the unobservable epochs from observable dates is an unsupervised learning problem, a common problem with many readily available algorithms. The idea is to choose the correspondence between epochs and failures, such that the likelihood of observing those closure dates is maximized. In the context of bank failures, the actual closure dates are assumed to be independent Gaussian random variables centered around the central date of that epoch. Then the observed official closure dates of all the failures can be used to infer the epoch they are associated with. This model is known as Gaussian Mixture Model (GMM) in machine learning community since the variables are generated from a mixture of different Gaussian distributions.

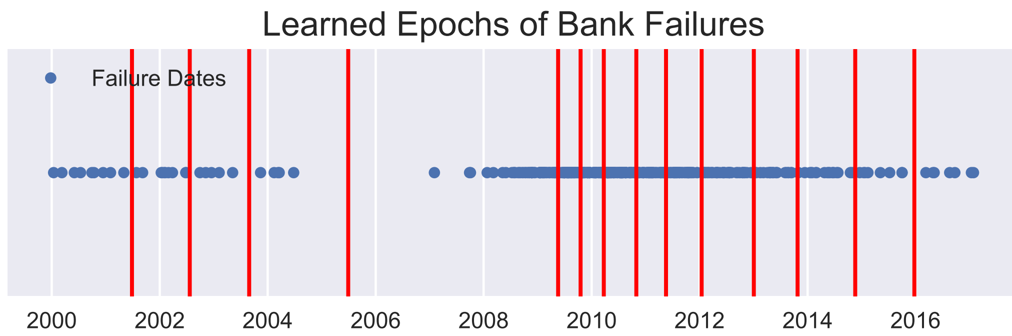


Figure 2.1: **Learned Epochs of Bank Failures:** This figure shows all failures since October 2000. Each dot corresponds to one bank failure. The dates are the official dates on which the failed bank ceased to operate as an entity. Vertical lines are the boundaries between epochs of failures. The epochs associated with the failures and their boundaries are learned using Gaussian Mixture Model (GMM).

I choose 15 to be the number of epochs so that each epoch lasts one year on average. Figure 2.2.3 shows the learned epochs associated with each failure. Table 2.4.1 reports some summary statistics regarding these epochs. I also varied the number of epochs from 10 to 30, finding that all the main results showed in the next section hold qualitatively. Appendix 2.B gives a more detailed description of this method and algorithm.

The algorithm also produces the boundary, or starting and ending dates, of each epoch. I then used the Summary of Deposits data to construct a bank-epoch panel. Peers of each bank is also identified from SOD data at the beginning of each epoch. Call Reports was used to construct all the accounting-based variables of interest, which were then matched to the bank-epoch panel. For all the failed banks, I used the last available Call Reports data before failure. The Bid Summary from FDIC's failed bank list was used, whenever available, to identify the acquirer and bid amount for each failed bank.

2.3 Hypothesis Development

To develop some intuition and hypotheses regarding the spillover effect of bank failures, I focus on the choice among different bidders and do not explicitly consider the liquidation alternative[6].

Consider an economy with many banks; they have branches in partially overlapping markets. Suppose now Bank Trouble has failed. FDIC will hold an auction for it, in which all banks in the economy can participate. What is the impact of this failure from the perspective of Bank Awesome, one competitor (or peer) of Bank Trouble? Different acquirers of Bank Trouble may generate very different implications for Bank Awesome's failure probability. Specifically, I discuss two cases: the acquirer is a competitor of Bank Awesome, and the acquirer is not a competitor of Bank Awesome before the failure.

Suppose in the first scenario, Bank Competitor wins the auction for Bank Trouble, and Bank Competitor is competing with Bank Awesome prior to Bank Trouble's failure. That is, Bank Awesome is competing with both the failed bank and the acquirer before the failure. Bank Competitor merges all existing branches, operations, and customer relations of Bank Trouble into itself. With fewer banks competing with Bank Awesome than before, it may become more profitable, because it now has more market power due to the consolidation of Bank Competitor and Bank Trouble. Thus, Bank Awesome becomes less likely to fail.

Next, consider another scenario, wherein Bank Noncompetitor wins the auction for Bank Trouble. Bank Noncompetitor did not compete with Bank Awesome before the failure. From Bank Awesome's perspective, there is no change in industrial organization structure; the number of competitors in its market effectively remains the same in the after the transaction. The only difference is that branches of Bank Trouble are now under the name of Bank Noncompetitor. From a pure industrial-organization

[6] Only 31 out of 563, or 5.5% of bank failures since October 2000 ended with liquidation.

perspective, no change in competition in the market is expected, thus no change in the failure probability of any bank which is a competitor of Bank Trouble but not a competitor of Bank Noncompetitor[7].

So far I have demonstrated that the competitive relationship between the acquirer of a failed bank and the affected banks has important implications, via a industrial-organization-based channel, on the failure probability of these affected banks. The overall spillover effect of bank failures averaged across different types of acquirers in different failed-bank transactions remains an empirical question, which crucially depends on which type of acquirer is dominating. I need to emphasize that I describe the above example and intuition to highlight a competitive channel of the bank failure spillover effect, which is the main focus of this paper. There are apparently other channels that generate the interdependency among bank failures.

In fact, the competitive relationship between an acquirer and a failed bank may also impact the observed spillover effect. I will also discuss the potential implications of two different scenarios of competitive relationship between the acquirer and the failed bank. Again consider the example in which Bank Trouble fails. What might the consequences be from Bank Awesome's perspective?

First suppose Bank Inside, which competes with Bank Trouble, wins the auction for Bank Trouble. Bank Inside, being in similar markets as Bank Trouble, is likely to have low information asymmetry with Bank Trouble. The information advantage of Bank Inside over other banks that are not in similar markets may come from several sources. Bank Inside may have a business relationship with Bank Trouble through, for example, borrowing and lending. Bank Inside is exposed to similar local economic conditions as Bank Trouble, thus has a better assessment of the common component of risk factors faced by Bank Trouble. Granja et al. (2017) find that acquirers are geographically closer to the target failed banks, compared to other bidders. They

[7] In the long run, the failure probability of these banks may increase because now they are facing competition from a larger bank: Bank Noncompetitor.

provide further evidence of information advantage coming from having similar real estate loan portfolios.

Bank Inside's winning the auction for Bank Trouble may suggest that the local economic conditions faced by Bank Trouble are favorable, and the failure is only due to idiosyncratic reasons. Affected banks such as Bank Awesome, a competitor of Bank Trouble, and thus in similar markets, are also likely to have favorable local economic conditions. Hence, Bank Inside's winning the auction is likely to predict a lower failure probability of Bank Awesome, because it has similar favorable economic conditions. Notice that the correlation between Bank Inside's being the acquirer and Bank Awesome's being less likely to fail is due to the selection of Bank Inside, which is not causal. That is, Bank Inside's winning the auction does not cause a lower failure probability of Bank Awesome; instead both events are the consequence of favorable local economic conditions. This is vastly different from the competitor v.s. noncompetitor acquirer case discussed earlier, in which the competitor acquirer winning the auction cause a lower failure probability of affected banks by augmenting the industrial organization structure they face.

2.4 Results

2.4.1 Descriptive Statistics

Table 2.4.1 panel A reports summary statistics on characteristics of banks in my sample. In particular, I separate the banks into four groups: *Failed, Survived, Bidders* and *Acquirers. Failed* are the banks that eventually fail in my sample period 2000 to 2016. *Survived* are the banks that did not fail by the end of the sample period. *Bidders* are the banks that have participated in auctions for the failed banks during the sample period. *Acquirers* are the banks that won any auction for a failed bank in the sample period. In total, there are 491 *Failed*, 8,080 *Survived*, 373 *Bidders,* and

220 *Acquirers.* I computed the time series average of each bank in these four groups. The reported summary statistics are computed using the cross-section of time series means of all the banks in my sample.

Noticeably, failed banks seemed to be larger than survived banks. This is due to failures of several very large banks during the recent financial crisis. The banks participating in auctions for failed banks are also significantly larger than average. Moreover, winners of these auctions tended to be the banks on the very right tail of the size distribution. Another interesting comparison is that the failed banks are much younger than other groups of banks. In other words, the hazard rate of banks seems to be largely decreasing. As I discussed earlier, the spillover effect of bank failures is transmitted in the bank network through banks operating in multiple markets or MSAs. The summary statistics show that a median bank only operates in about one MSA, and an average bank operates in about two MSAs. Therefore, the larger banks play a crucial role in transmitting the spillover effect, as well as the identification of the spillover effect.

Table 2.4.1 panel B reports some statistics about the learned failure epochs. The duration of each epoch has an average of 407 days and median 324 days. This is by design since I chose to have 15 epochs, allowing each epoch a length of around one year. The longest epoch, with 151 failures, lasts 1419 days, which covers the entire financial crisis. It is worth pointing out that the failures during the recent financial crisis always get classified into one epoch as long as the total number of epochs is not too large.

Here I report some summary statistics about the bank network, which are not included in the table. The density of the network is 0.016, which means only 1.6% of potential edges are connected. In theory, the peer effect can be identified within a network as long as the network has a density of less than 1. The network in this research in relatively sparse, which facilitates the identification of the spillover effect

Panel A: Banks

	Failed			Not Failed			Bidders			Acquirers		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Size	5,099	211	53,600	1,598	183	19,400	4,272	604	17,900	6,369	760	22,800
Capad	0.090	0.083	0.033	0.118	0.099	0.085	0.111	0.101	0.032	0.112	0.103	0.032
Earn	-0.010	-0.008	0.017	0.005	0.007	0.124	0.007	0.008	0.010	0.008	0.008	0.009
Liq	-0.024	-0.017	0.058	-0.015	-0.08	0.074	0.005	0.003	0.041	0.008	0.005	0.035
Age	34	17	38	60	57	46	57	50	45	58	48	45
Deposits	1,829	136	19,400	793	106	8,469	2,396	332	9,649	3,572	414	12,300
# Branches	36	6	362	22	6	155	83	18	261	122	26	330
# MSAs	2.67	1.00	11.68	2.09	1.00	6.11	6.32	2.00	13.95	8.55	3.00	17.08
# Peers	254	186	371	186	102	242	374	237	461	434	278	538
# Failed Peers	3.00	1.87	3.20	0.92	0.29	1.83	2.42	1.40	3.07	2.67	1.53	3.40

Panel B: Failure Epochs

	Mean	Median	Std	Min	Max
# Failures	35	18	37	5	115
Duration	407	324	349	151	1419

Table 2.1: **Summary Statistics:** This table reports summary statistics of the sample. Banks are categorized into four not-mutually-exclusive groups: Failed are banks that failed; Not Failed are banks that had not failed by the end of the sample period; Bidders are banks that have participated in any failed bank auctions; Acquirers are banks that have won any failed bank auction. Size is the total assets in millions. Capad is a capital adequacy measure defined as total equity divided by total assets. Earn is net income divided by total assets. Liq is liquidity defined as net purchase of federal funds divided by total assets. Age is the number of years since a bank was chartered. Deposits is the total deposits in millions. Panel B reports some statistics on the failure epochs learned using the Gaussian Mixture Model. Duration is the number of days of an epoch.

of failures. The network has a diameter of 5, which means any two banks are only separated by at most five other banks.

2.4.2 Average Spillover Effects

Table 2.4.2 reports several different specifications in which I attempt to identify the average spillover effects of bank failures. I present both OLS and Logit model results. In Logit regressions, I pass everything on the right hand side of the baseline model 2.1 through a logistic function. I use Logit models to generate reasonable failure probability predictions, since OLS can generate predicted probability out of $[0, 1]$. On the other hand, OLS acts as a robustness test to Logit models, assuring that the specific form of nonlinearity of Logit models is not driving the results.

In Columns (1) and (2), the only regressor is the total number of failed peers ($\# \, Failed \, Peers$) for a given bank in a given epoch. The results show a strong positive correlation between one bank's failure and its peer's failure. This is not surprising, since large-scale economic downturn is believed to be a dominating contributor to bank failures.

In Columns (3) and (4), I include more bank-level controls as regressors, including the size and age of a bank, as well as the average size and age of its peers[8]. Bank failure is still strongly positively correlated with peers failure, even when these variables are controlled. Two other phenomena are worth pointing out: failure probability is higher for younger banks, and for banks with larger peers. The latter may reflect the competitive pressure caused by larger peers.

In Columns (5) and (6), I include $MSA \times Epoch$ controls. As argued in Section 3.2.2, these controls are critical in the context of bank failures because of the so-called

[8]The choice of only including size and age as control variables is motivated by the fact that the peer effect model requires that the control variables to be plausibly exogenous. Other financial conditions, while likely to be correlated with failure probability, are endogenous to the interactions among banks, similar to failure probability. However, in practice, including other variables such as ROA, capital ratio, liquidity ratio, deposit growth, etc. gives the same qualitative results as those reported in the table.

Variables	(1) *Fail*	(2) *Fail*	(3) *Fail*	(4) *Fail*	(5) *Fail*	(6) *Fail*
Model	OLS	Logit	OLS	Logit	OLS	Logit
$\# Failed\, Peers$	0.0022***	0.0812***	0.0020***	0.0641***	-0.0321***	-2.3510***
	(0.000)	(0.005)	(0.000)	(0.006)	(0.002)	(0.117)
$Size$			-0.0002	0.0056	0.0010***	0.0178
			(0.000)	(0.003)	(0.000)	(0.051)
Age			-0.0006**	-0.0860**	-0.0010***	-0.2017***
			(0.000)	(0.039)	(0.000)	(0.049)
$Peer\, Mean\, Size$			0.0013***	0.2363***	0.0038***	0.0767
			(0.000)	(0.054)	(0.000)	(0.170)
$Peer\, Mean\, Age$			-0.0055***	-1.2655***	-0.0215***	-2.8928***
			(0.001)	(0.101)	(0.001)	(0.366)
$MSA \times Epoch$	No	No	No	No	Yes	Yes
$Observations$	82,747	82,747	82,747	82,747	82,747	82,747
$Pseudo/Adj. - R^2$	0.01	0.03	0.01	0.08	0.06	0.61

Table 2.2: **Spillover Effects of Peer Bank Failures**: This table presents the results of variations of $F_{it} = \alpha + \beta \sum_{j \in P_i} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it}$. F_{it} is an indicator variable equal to 1 if bank i failed at epoch t. P_{it} is the set of all banks that are peers of bank i. X_{it} is a vector of control variables. M_{it} is the set of MSAs bank i has branches in at epoch t. $\# Failed\, Peers$ is the total number of failed peers, or $\sum_{j \in P_i} F_{jt}$ in the equation. Even columns report the Logit model version of the equation, in which the right-hand side of the equation is passed through a logistic function. The sample includes all banks from 2000 to 2014. Failed banks are defined as those appearing on the FDIC failed bank list. Standard errors are in parentheses. All standard errors are clustered at bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

correlated effects. It is clear that more failed peers lead to lower failure probability on average, after the correlated effects, or MSA level macroeconomic shocks in each epoch, are controlled for. Another slightly different interpretation of the result is that one failed bank lowers the average failure probability among all its peers. One potential concern is that other macroeconomic shocks may be occurring within finer geographical regions, such as counties or cities. I argue that this concern does not affect my results qualitatively. The macroeconomic shocks in finer geographical regions would bias the coefficient before $\#Failed\,Peers$ toward zero, since these shocks lead to a positive correlation of failure among banks present in those regions. In other words, the negative spillover effect of failed peers seen in the table should be larger in magnitude, if macroeconomic shocks in finer geographical regions exist.

To better visualize the results, I plotted the predicted failure probability against the total number of failed peers, while keeping other control variables at their sample means, using the Logit model. The result is shown in Figure 2.4.2. The spillover effect of peer failure is tremendous in magnitude. One failed peer makes an average bank ten times less likely to fail.

What does the negative spillover effect of bank failures I present here imply for the FDIC's current resolution policy? The results show there may be an indirect monetary benefit through the spillover effects that the current policy is not taking into account. The current resolution policy treats each failure as a standalone event. FDIC resolution choices that minimize the monetary cost of each bank failure separately are likely not cost minimizing, given the existence of an indirect spillover cost. In view of the large spillover effect on failure probability, and the usually high cost of resolution, reduction in total resolution cost over time could be achieved by choosing the options with the lowest combined cost: the direct monetary cost and the indirect benefit or cost due to spillover. The results so far do not provide clear guidance on how to choose among resolution alternatives with the lowest combined cost. However, the discussion

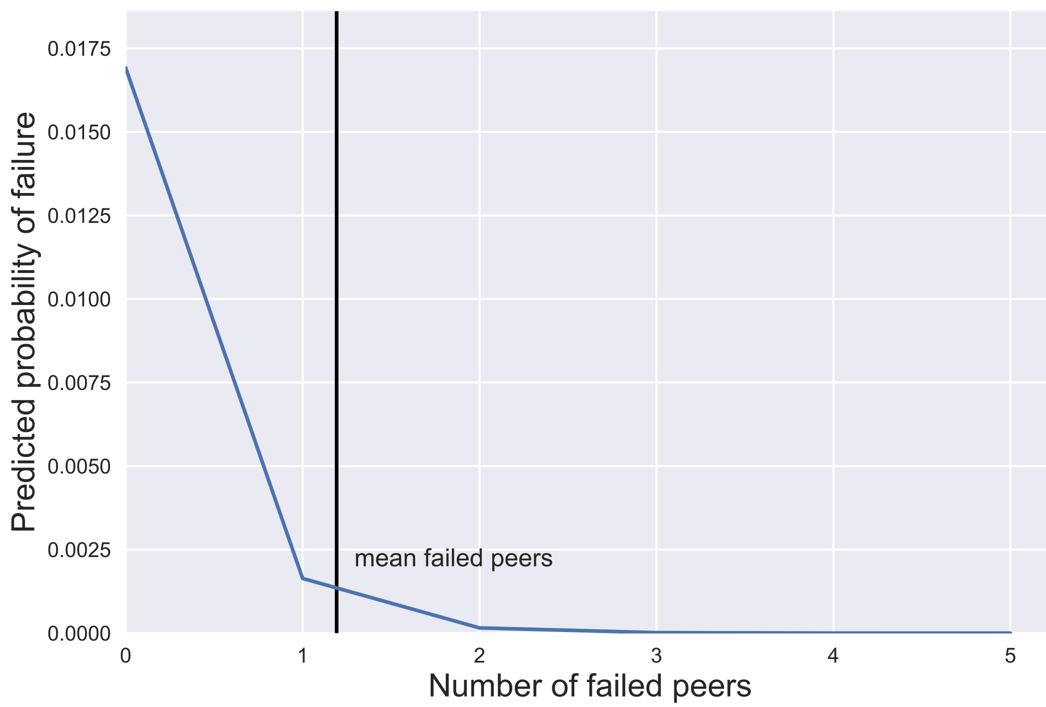


Figure 2.2: **Predicted Failure Probability Conditional on Peer Failures:** This figure shows the predicted failure probability as a function of the total number of failed peers. The prediction is done using a Logit model, including $Size$, Age, $Peer\,Mean\,Size$ and $Peer\,Mean\,Age$ as controls. All control variables are set at the sample mean. The vertical line represents the sample average number of failed peers.

in Section 2.3 offers some hint for further analysis seeking such resolution alternatives. It is intuitive to think that the competitive positions of different potential acquirers of a failed bank can have different spillover effects, since the industrial organization structure will be drastically different if any one of these potential acquirers actually ends up acquiring the failed bank. Under the current resolution policy, the acquirer will be the bank with the lowest direct monetary cost. But the acquirer with the lowest combined cost may be another bank, one with slightly higher direct monetary cost but much lower spillover cost. I explore in more detail the heterogeneity in spillover effects among different types of acquirers in the next section.

Table 2.4.2 reports the impact of peer failures on various aspects of a bank, providing clues as to how the spillover effect of peer failures eventually manifests itself as lower failure probability for an affected bank. Results in Column (1)indicate that peer failures lead to higher return on equity controlling for other bank-level variables and $MSA \times Epoch$ fixed effects. In other words, peer banks of a failed bank become more profitable following the failure. As discussed above, this is not caused by lower competitive pressure as a result of the exit of the failed bank, since almost always another healthy institution will acquire it. Column (2) shows that peer failures also lead to better capital adequacy. This is also consistent with lower failure probability. Column (3) shows that peer failures seem to lead to higher deposit growth on average for banks affected. If we use the growth rate of deposit as an indicator for bank's well being, then the result on deposit growth suggest that the banks affected by peer failures are better off. Column (4) suggests that affected banks' assets become less liquid owing to peer failures.

2.4.3 Heterogeneous Spillover Effects

This section presents and discusses the heterogeneous spillover effects of different types of bank failures. As discussed in Section 2.3, the positions of acquirers of failed

Variables	(1) *Earn*	(2) *Capad*	(3) ΔDep	(4) *Liq*
$\# Failed\,Peers$	0.0014***	0.0092***	0.0376***	-0.0031***
	(0.000)	(0.000)	(0.010)	(0.001)
Size	0.0020***	-0.0091***	-0.0459***	0.0192***
	(0.000)	(0.000)	(0.004)	(0.000)
Age	0.0022***	-0.0048***	-0.2803***	0.0035***
	(0.000)	(0.000)	(0.005)	(0.000)
Peer Mean Size	-0.0017***	0.0036***	-0.0251***	-0.0023***
	(0.000)	(0.000)	(0.007)	(0.000)
Peer Mean Age	0.0034***	-0.0004	0.0233	0.0117***
	(0.000)	(0.001)	(0.017)	(0.001)
$MSA \times Epoch$	Yes	Yes	Yes	Yes
Observations	82,747	82,747	82,747	82,747
$Adj. - R^2$	0.04	0.08	0.16	0.14

Table 2.3: **Impacts of Peer Bank Failures**: This table presents the results of variations of $Y_{it} = \alpha + \beta \sum_{j \in P_i} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it}$. Y_{it} is an outcome variable of bank i at epoch t . P_{it} is the set of all banks that are peers of bank i. X_{it} is a vector of control variables. M_{it} is the set of MSAs bank i has branches in at epoch t. $\# Failed\,Peers$ is the total number of failed peers, or $\sum_{j \in P_i} F_{jt}$ in the equation. *Earn* is equal to net income divided by total assets. *Capad* is defined as total equity divided by total assets. ΔDep is the percentage change of total deposits between the year failure happened and 1 year after that. It is winsorized at 99th percentile. *Liq* is a liquidity measure, defined as net purchase of fed funds divided by total assets. The sample includes all banks from 2000 to 2014. Failed banks are defined as those banks which appeared on FDIC failed bank list. Standard errors are in parentheses. All standard errors are clustered at bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

banks, and their competitive relationships with other affected banks have important implications for the direction and magnitude of the spillover effect. Identifying heterogeneity in the effect sheds light on the economic mechanisms through which spillover occurs. Moreover, understanding the heterogeneous effect aids effort to better assess the unintended cost or benefit of the current least cost resolution policy, and potentially improve it.

At least three banks are involved when assessing a bank failure: the failed Bank A, an affected bank B, which competes with Bank A, and the acquirer Bank C, which acquires Bank A. When Bank C is also a peer of Bank B, from Bank B's perspective, there is a consolidation among its competitors following the acquisition. On the other hand, when Bank C is not a peer of Bank B, there is no consolidation among its competitors after the transaction. I call the former type of acquirers *Peer Acquirers* and the latter type *Nonpeer Acquirers*. There are also two types of competitive relationship between Bank A and Bank C. I call Bank C *Inside Acquirer* when it is also a peer of Bank A, and *Outside Acquirer* when it is not.

Following Section 2.3, I explore heterogeneity in the spillover effect along two dimensions: *Peer Acquirers* vs. *Nonpeer Acquirers*, and *Inside Acquirers* vs. *Outside Acquirers*.

Peer Acquirers v.s. Nonpeer Acquirers

Table 2.4.3 reports the heterogeneous spillover effects along these two dimensions. Columns (1), (2) and (3) report the OLS and Logit results for *Peer Acquirers* vs. *Nonpeer Acquirers*. Specifically, *# Peer Acquirers* is the total number of peer failures where the failed peer is acquired by a bank that is a peer of the observed bank. Column (1) reports the effect on failure probability of *Peer Acquirers* and *Nonpeer Acquirers* separately. Peer failures with *Peer Acquirers* lead to lower failure probability while peer failures with *Nonpeer Acquirers* actually lead to higher failure probability. The difference in the effects between these two types of acquirers is significant, as shown

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	*Fail*	*Fail*	*Fail*	*Fail*	*Fail*
Model	OLS	OLS	Logit	OLS	OLS	Logit
# Peer Acquirers	-0.1303***	-0.1848***	-1.0767***			
	(0.009)	(0.003)	(0.235)			
# Nonpeer Acquirers	0.0545***					
	(0.004)					
# Inside Acquirers				-0.0589***	-0.0763***	0.1232
				(0.005)	(0.002)	(0.186)
# Outside Acquirers				0.0174***		
				(0.003)		
# Classifiable Acquirers	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
$MSA \times Epoch$	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,518	82,518	82,518	82,518	82,518	82,518
$Pseudo/Adj. - R^2$	0.12	0.12	0.53	0.08	0.08	0.33

Table 2.4: **Heterogeneous Spillover Effects of Peer Bank Failures**: This table presents the results of variations of $F_{it} = \alpha + \beta_1 \sum_{j \in P_i} Type_{1j} F_{jt} + \beta_2 \sum_{j \in P_i} Type_{2j} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it}$. F_{it} is an indicator variable equal to 1 if bank i failed at epoch t. P_{it} is the set of all banks that are peers of bank i. $Type_{1j}$ and $Type_{2j}$ are indicator variables for the type of acquirers associated with failure of bank j. For example, when looking at peer v.s. nonpeer acquirers, $Type_1 = 1$ for failures with peer acquirers, and 0 for failures with nonpeer acquirers. X_{it} is a vector of control variables. *Controls* in the table include all X_{it} and X_{jt}, i.e., size, age, peer's mean size and peer's mean age. M_{it} is the set of MSAs bank i has branches in at epoch t. *# Failed Peers* is the total number of failed peers, or $\sum_{j \in P_i} F_{jt}$ in the equation. *# Peer Acquirers* is the total number of peer failures whose acquirer is also peer of bank i. *# Nonpeer Acquirers* is the total number of peer failures whose acquirer is not peer of bank i. *# Inside Acquirers* is the total number of peer failures whose acquirer is a peer of the failed bank. *# Outside Acquirers* is the total number of peer failures whose acquirer is not a peer of the failed bank. *# Classifiable Acquirers* is the total number of failures with the two corresponding acquirer types combined. Column (3) and (6) report the Logit model version of the equation, where the right hand side of the equation is passed through a logistic function. The sample includes all banks from 2000 to 2014. Failed banks are defined as those appearing on the FDIC failed bank list. Standard errors are in parentheses. All standard errors are clustered at bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

in Column (2), where the coefficient before # *Peer Acquirers* measures the difference in the spillover effects between *Peer Acquirers* and *Nonpeer Acquirers*. Column (3) reports the results using a Logit model. The difference between the two types of acquirers in terms of effect on failure probability is qualitatively the same. This Logit model allows me to generate predicted failure probability conditional on the total number of peer failures with *Peer Acquirers*.

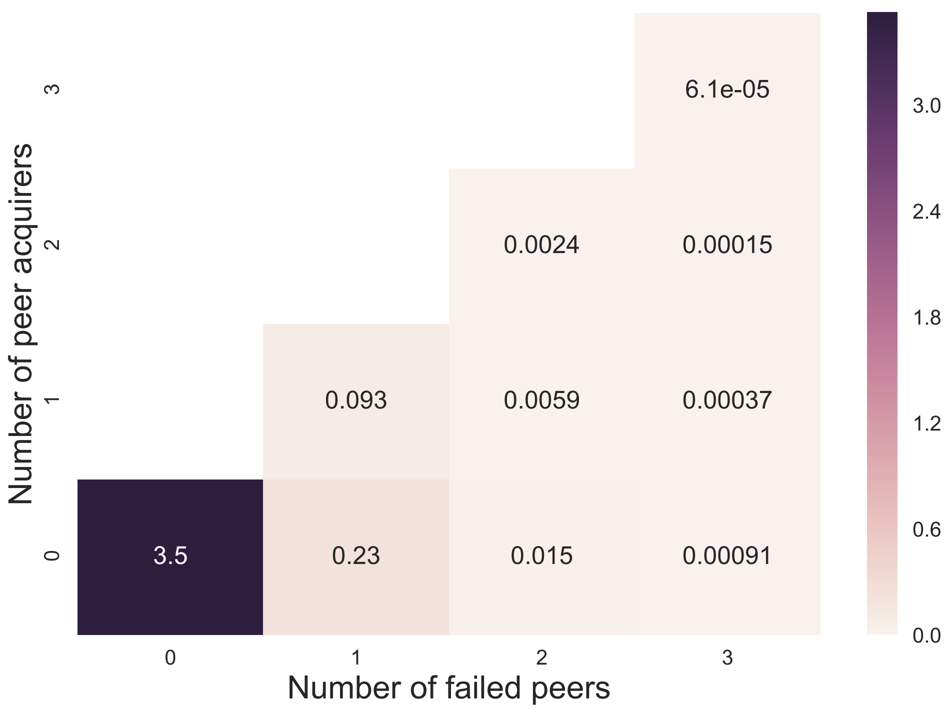


Figure 2.3: **Predicted Failure Probability with Peer Acquirers**: This figure shows the predicted probability of failure using a Logit model, conditional on different compositions of acquirer types. The total number of failed peers is on the horizontal axis. The total number of failed peers with peer acquirers is on the vertical axis. The total number of nonpeer acquirers is the difference between the total number of failed peers, and the total number of peer acquirers. All other control variables are set at the sample mean. The numbers in the boxes are predicted failure probability in basis points. The boxes are also color coded so that a darker color indicates higher failure probability.

The results are visualized as a heatmap in Figure 2.4.3. The horizontal axis represents the total number of failed peers, regardless of acquirer type, whereas the vertical axis represents the total number of failed peers with *Peer Acquirers*. All predicted probabilities are in basis points. In keeping with the results reported above, the failure probability drops with more failed peers. More importantly, the failure probability is even lower when the acquirers of the failed peers consist of more *Peer Acquirers*. The marginal effect is economically large: for every additional peer acquirer, the failure probability drops by half.

The *Peer Acquirers* v.s. *Nonpeer Acquirers* results are consistent with the presence of a competition channel. The affected bank gains market power when consolidation of competitors occurs through a peer bank's acquiring a failed peer. Affected banks can sustain a higher monopolistic profit, thus lowering failure probability.

To see what aspects of banks' operations are impacted by the two different types of acquirers, I again investigated the changes in several operation-related variables.

Table 2.4.3 presents the results. All coefficients of *# Peer Acquirers* measure the difference in impact on the outcome variables of *Peer Acquirers* over *Nonpeer Acquirers*. Column (1) shows that relative to *Nonpeer Acquirers*, failures with *Peer Acquirers* lead to a higher increase in earnings, suggesting banks affected by failures with *Peer Acquirers* become more profitable, thus contributing to a lower failure probability. Column (2) suggests that banks that are affected by failures with *Peer Acquirers* become better capitalized following the failures. Column (3) indicates that failures with *Peer Acquirers* lead to lower deposit growth of affected peer banks, relative to banks affected by *Nonpeer Acquirers* , though the difference is not significant. As discussed earlier, banks facing *Peer Acquirers* and *Nonpeer Acquirers* are subject to drastically different changes in industrial organization structure: banks facing *Peer Acquirers* see a consolidation of banks, leading to higher market power. According to this mechanism, affected banks are likely to tighten their credit supply to

Variables	(1) $Earn$	(2) $Capad$	(3) ΔDep	(4) Liq
$\#\,Peer\,Acquirers$	0.0117***	0.0121***	-0.0495	0.0074***
	(0.001)	(0.002)	(0.041)	(0.002)
$\#\,Failed\,Peers$	0.0007***	0.0085***	0.0411***	-0.0036***
	(0.000)	(0.001)	(0.010)	(0.001)
$Controls$	Yes	Yes	Yes	Yes
$MSA \times Epoch$	Yes	Yes	Yes	Yes
$Observations$	82,518	82,518	82,518	82,518
$Adj. - R^2$	0.04	0.08	0.16	0.14

Table 2.5: **Heterogeneous Impact of Peer and Nonpeer Acquirers**: This table presents the results of variations of $Y_{it} = \alpha + \beta_1 \sum_{j \in P_i} Peer_{ijt} F_{jt} + \beta_2 \sum_{j \in P_i} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it}$. Y_{it} is an outcome variable of bank i at epoch t . P_{it} is the set of all banks that are peers of bank i. X_{it} is a vector of control variables. $Controls$ in the table include all X_{it} and X_{jt}, i.e., size, age, peer's mean size and peer's mean age. M_{it} is the set of MSAs bank i has branches in at epoch t. $Peer_{ijt}$ is an indicator variable equal to one if bank i and bank j are peers at epoch t. $\#\,Failed\,Peers$ is the total number of failed peers, or $\sum_{j \in P_i} F_{jt}$ in the equation. $Earn$ is equal to net income divided by total assets. $Capad$ is defined as total equity divided by total assets. ΔDep is the percentage change of total deposits between the year failure happened and one year after that. It is winsorized at the 99th percentile. Liq is a liquidity measure, defined as net purchase of fed funds divided by total assets. The sample includes all banks from 2000 to 2014. Failed banks are defined as those appearing on the FDIC failed bank list. Standard errors are in parentheses. All standard errors are clustered at bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

boost lending rates and profits. As a result of tightened credit supply, deposit growth of these banks is likely to drop as well because they do not need as much deposit to lend out. However, this table does not show a significant difference between banks facing $Peer\,Acquirers$ and $Nonpeer\,Acquirers$, in terms of changes in deposit growth. This lack of difference could be due to the fact that the supply of credit and the demand for deposit are not closely connected. Column (4) of Table 2.4.3 shows that banks associated with $Peer\,Acquirers$ become more liquid as a result of a focal failure, relative to banks affected by $Nonpeer\,Acquirers$. The results reported in Table 2.4.3 and Table 2.4.3 suggest that $Peer\,Acquirers$ lead to better performance and lower failure probability for affected banks competing with failed banks. In other words, these banks seem to benefit from the consolidation in their markets, a finding broadly consistent with the competition channel. The next section provides more evidence of this channel.

Mortgage Loan Lending

So far, I have proposed a competition channel as the transmission mechanism of the spillover effect given the evidence that peer acquirers and nonpeer acquirers have a drastically different impact on banks affected by a failure. This section offers additional evidence of the competition channel through the lens of mortgage lending activities. The hypothesis follows from earlier discussion in Section 2.3 and Section 2.4.3: from the perspective of a bank affected by the failure of a competing bank, the acquirer's being a peer at the same time leads to bank consolidation in the market, which increases the market power of affected banks according to classical industrial organization theories. In this section, I show that higher market power manifests itself as tightened mortgage lending. The intuition is that with fewer banks after the acquisition, banks engaging in Cournot competition can lower their supply of credit, charge higher lending rates, and thus realize higher profit. In other words, the hypothesis here is that acquisitions by peer acquirers should lead to a drop in mortgage loan supply and an increase in loan rates by affected banks on average. While the lending rates are hard to obtain, the quantity of mortgage loan origination is observable through the HMDA data set.

To test the hypothesis mentioned above, I first extracted bank-year variables on lending activities from the HMDA data. Two main variables are of interest: total loan amount and total number of originations. Total loan amount is simply the sum of all loans originated by a bank in a given year. Total number of originations is the total number of loans originated by a bank in a given year. In addition to the levels of these two variables, I also computed growth rates. Borrower income, which can be used to see if there is any shift in borrowers' characteristics, was also observable from HMDA. This bank-year mortgage lending sample was matched with the full sample used in all previous exercises. It turns out that less than half, or 4,103 of the banks in my full sample, have mortgage lending activities. The final merged sample consists of 34,355 bank-year observations.

Ideally, I would have implemented the regression specification in equation 2.1, using the mortgage lending variables as the dependent variable. However, a numerical complication arises here due to the $MSA \times Epoch$ fixed effects. Controlling for these fixed effects requires over 6,000 dummy variables. This generates numerical difficulty since these dummy variables are close to colinear. The problem becomes more pronounced when the number of observations is lower. In fact, standard statistical packages will complain about the singularity problem when trying to invert the variance-covariance matrix.

This problem necessitated compressing the vectors representing the MSA presence of each bank to much lower dimensional vectors. One candidate method was to implement a Principal Component Analysis on the matrix representing MSA presence of all banks and then use the loadings on the top principal components as the variables describing the locations of each bank. The intuition is that the principal components are clusters of MSAs, and the loadings on these principal components of each bank can be thought of as the exposure to these MSA clusters. The compression introduces noise in exchange for better numerical stability. Therefore, the objective of the compression method should be to preserve as much information as possible for any given number of compressed dimensions. In this study, I trained an Autoencoder using the MSA matrices, and then used it to generate a lower dimensional representation of the MSA vector of each bank. Specifically, I choose 25 as the number of dimensions in the compressed location representations. The trained Autoencoder can reconstruct over 80% of the variation in the original MSA matrix. As a comparison, the top 25 principal components can only capture 50% of the variation. Appendix 2.C describes the details of this method.

Table 2.4.3 reports the regression results. Columns (1) and (2) use denial rates and growth in denial rates as dependent variables. We can see in both columns that banks affected by peer acquirers appear to reduce the mortgage loan supply by denying more loan applications. Columns (3) and (4) look at total mortgage loan origination. The results show a significant decrease in total loan origination amount for banks affected by peer acquirers. All these results are consistent with the existence of a the competition channel: consolidation of banks leads to higher market power, and then to lower mortgage loan supply. Column (5) shows that there does not seem to be any significant shift in applicant profiles.

Inside Acquirers v.s. Outside Acquirers

In Columns (3), (4) and (5) of Table 2.4.3, I look at *Inside Acquirers* v.s. *Outside Acquirers*. *# Inside Acquirers* is the total number of cases in which a failed peers is acquired by a bank that is a peer to the failed bank. Column (3) reports the spillover effects for *Inside Acquirers* and *Outside Acquirers* separately. We can clearly see

Variables	(1) *Denial*	(2) Δ*Denial*	(3) *Loan Amt*	(4) Δ*Loan Amt*	(5) *Med Income*
# Peer Acquirers	0.0032**	0.0206**	-35.1078	-0.0149**	0.1385
	(0.001)	(0.010)	(30.103)	(0.007)	(1.018)
# Failed Peers	-0.0008	-0.0076	41.0441	0.0003	0.4262
	(0.001)	(0.005)	(25.222)	(0.004)	(0.610)
Controls	Yes	Yes	Yes	Yes	Yes
Location $\times$ *Epoch*	Yes	Yes	Yes	Yes	Yes
Observations	34,355	34,355	34,355	34,355	34,355
$Adj. - R^2$	0.01	0.01	0.10	0.09	0.08

Table 2.6: **Heterogeneous Impact on Mortgage Lending:** This table presents the results of $Y_{it} = \alpha + \beta_1 \sum_{j \in P_i} Peer_{ijt} F_{jt} + \beta_2 \sum_{j \in P_i} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{l=1}^{25} \delta_{lt} L_{ilt} + \epsilon_{it}$. Y_{it} is an outcome variable of bank i at epoch t . P_{it} is the set of all banks that are peers of bank i. X_{it} is a vector of control variables. *Controls* in the table include all X_{it} and X_{jt}, i.e., size, age, peer's mean size and peer's mean age. L_{ilt} is the lth element in the encoding of i's MSA locations at epoch t. $Peer_{ijt}$ is an indicator variable equal to 1 if bank i and bank j are peers at epoch t. *# Failed Peers* is the total number of failed peers, or $\sum_{j \in P_i} F_{jt}$ in the equation. *Denial* is ratio of denied mortgage loan applications over the total number of applications. Δ*Denial* is the growth rate of *Denial*, defined as $\frac{Denial_t - Denial_{t-1}}{(Denial_t + Denial_{t-1})/2}$. *Loan Amt* is the total dollar amount of mortgage loans originated in millions. Δ*Loan Amt* is the growth rate of *Loan Amt*, which is defined similarly as Δ*Denial*. The sample includes all banks with any mortgage lending activity from 2000 to 2014. Failed banks are defined as those appearing on the FDIC failed bank list. Standard errors are in parentheses. All standard errors are clustered at bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

Inside Acquirers leads to a lower probability of failure for affected banks, while *Outside Acquirers* leads to higher failure probability. In Column (4), the coefficient before # *Inside Acquirers* measures the difference in spillover effect of *Inside Acquirers* over *Outside Acquirers*, which suggests the difference between these two types of acquirers in terms of spillover effects is significant. However, the results do not seem robust: the OLS model indicates that *Inside Acquirers* leads to lower failure probability than *Outside Acquirers*, but the Logit model suggests there is little difference between *Inside Acquirers* and *Outside Acquirers*.

Again, to visualize the results of the Logit model, I computed the predicted probability of failure with a different number of *Inside Acquirers* among all peer failures. The predicted probabilities are graphed in Figure 2.4.3. The total number of peer failures is on the horizontal axis, and the number of *Inside Acquirers* is on the vertical axis. All the predicted probabilities are in basis points. Moving from left to right on the horizontal axis shows that one additional failed peer significantly lowers the failure probability, consistently with previous results. A roughly 40% drop in failure probability occurs with each additional failed peers. However, the figure shows little change in predicted failure probability when more peer failures have *Inside Acquirers*, when tracked from bottom to top for any given number of failed peers.

The *Inside Acquirers* vs. *Outside Acquirers* results show some evidence that failures with inside acquirers tend to make affected banks even less likely to fail, relative to failures with outside acquirers. Inside acquirers may have superior information about the economic environment a failed bank is operating in and may only acquire the failed bank when they deem local economic conditions sufficiently favorable. Granja et al. (2017) document that the acquirers of failed banks are geographically closer to their targets. They also provide evidence that these acquirers have an information advantage over other bidders. One such information advantage comes

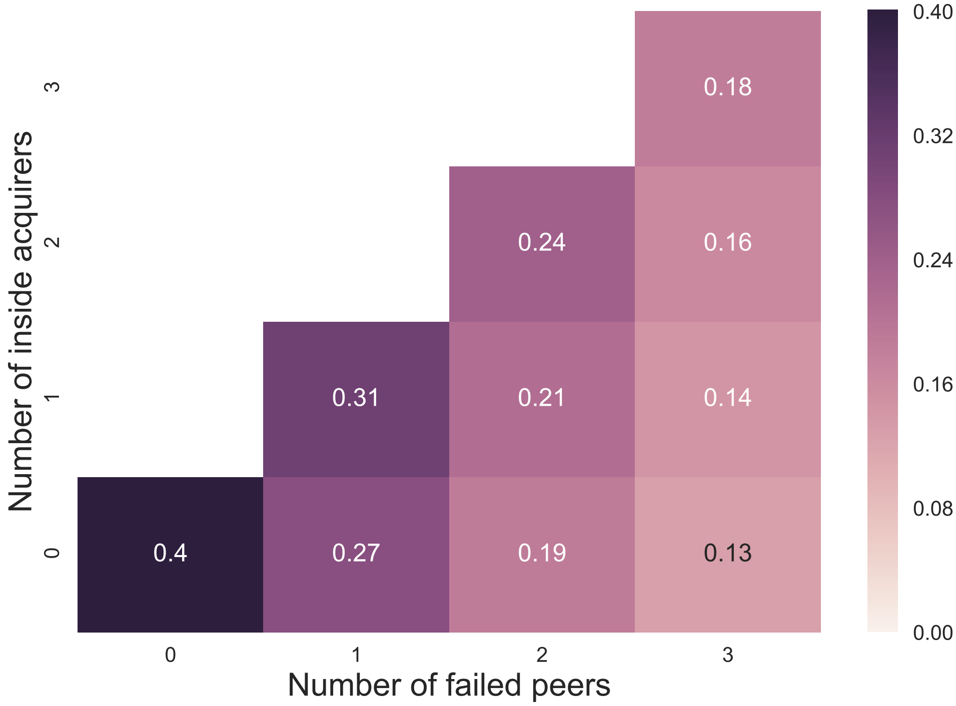


Figure 2.4: **Predicted Failure Probability with Inside Acquirers**: This figure shows the predicted probability of failure using a Logit model, conditional on different compositions of acquirer types. The total number of failed peers is on the horizontal axis. The total number of failed peers with inside acquirers is on the vertical axis. The total number of outside acquirers is the difference between the total number of failed peers, and the total number of inside acquirers. All other control variables are set at the sample mean. The numbers in the boxes are predicted failure probability in basis points. The boxes are also color coded so that a darker color indicates higher failure probability.

from the fact that the acquirers and targets have similar real estate loan portfolios. The present results are also consistent with this argument, in that the banks affected by a failure have similar real estate loan portfolios as well. However, this information advantage and selection channel are again unlikely to comprise the main driving force of the results I document, since I controlled for $MSA \times Epoch$ fixed effects.

Variables	(1) $Earn$	(2) $Capad$	(3) ΔDep	(4) Liq
$\#Inside\,Acquirers$	-0.004	0.0019	0.0086	0.0079***
	(0.010)	(0.001)	(0.025)	(0.001)
$\#Failed\,Peers$	0.0015***	0.0090***	0.0372***	-0.0040***
	(0.000)	(0.001)	(0.010)	(0.001)
$Controls$	Yes	Yes	Yes	Yes
$MSA \times Epoch$	Yes	Yes	Yes	Yes
$Observations$	82,518	82,518	82,518	82,518
$Adj.-R^2$	0.04	0.08	0.16	0.14

Table 2.7: **Heterogeneous Impact of Inside and Outside Acquirers**: This table presents the results of variations of $Y_{it} = \alpha + \beta_1 \sum_{j \in P_i} Inside_{jt} F_{jt} + \beta_2 \sum_{j \in P_i} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it}$. Y_{it} is an outcome variable of bank i at epoch t . P_{it} is the set of all banks that are peers of bank i. X_{it} is a vector of control variables. $Controls$ in the table include all X_{it} and X_{jt}, i.e., size, age, peer's mean size and peer's mean age. M_{it} is the set of MSAs bank i has branches in at epoch t. $Inside_{jt}$ is an indicator variable equal to 1 if bank j is acquired by a peer bank after failure at epoch t. $\#Failed\,Peers$ is the total number of failed peers, or $\sum_{j \in P_i} F_{jt}$ in the equation. $Earn$ is equal to net income divided by total assets. $Capad$ is defined as total equity divided by total assets. ΔDep is the percentage change of total deposits between the year failure happened and 1 year after that. It is winsorized at the 99th percentile. Liq is liquidity defined as net purchase of fed funds divided by total assets. The sample includes all banks from 2000 to 2014. Failed banks are defined as those appearing on the FDIC failed bank list. Standard errors are in parentheses. All standard errors are clustered at bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

Table 2.4.3 reports the impact of failures with $Inside\,Acquirers$ v.s. failures with $Outside\,Acquirers$ on some variables capturing banks' operation. The coefficients of $\#Inside\,Acquirers$ measure the difference in spillover effects on the corresponding operation variable between failures with $Inside\,Acquirers$ and failures with $Outside\, Acquirers$. The comparison between these two types of acquirers is clearly not as pronounced as the comparison between $Peer\, Acquirers$ and $Nonpeer\, Acquirers$. Column (1) shows little difference in the impact on earnings between the two types of acquirers. Column (2) indicates the effects of failures with $Inside\, Acquirers$ and $Outside\, Acquirers$ on capital adequacy do not differ significantly as well. Column (4)does show that banks affected by failures with $Inside\, Acquirers$ experience better liquidity.

Heterogeneous Exposure to Peer Failure

In the discussion and results presented so far, I have treated all connections, or competitive relationships, between all pairs of banks as the same. In other words, I only took into account only the existence of competition between two banks, but not its extent. To provide more evidence for a competition channel for the bank failure spillover effect, I exploited the heterogeneity in the exposure to peer failures, based on how competitive the affected banks and the failed bank were. The intuition is as follows: Suppose Bank A failed and got acquired by Bank C. How is Bank B, a peer of Bank A, affected? If Bank B's entire operation is in the markets where Bank A and Bank C operate, Bank B should be strongly impacted by Bank A's failure and subsequent acquisition by Bank C. On the contrary, if only a small part of Bank A's operation is in the markets where Bank B and Bank C are, little impact on Bank A should be seen.

Concretely, I generalize the baseline model in equation 2.1 to accommodate heterogeneous spillover effect β.

$$F_{it} = \alpha + \sum_{j \in P_i} \beta_{ij} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it} \tag{2.2}$$

In particular the heterogeneous spillover effect β_{ij} takes the following form,

$$\beta_{ij} = \theta_0 + \theta_1 \frac{\sum_{m \in M_{ct}} Dep_{imt}}{\sum_{m \in M_{it}} Dep_{imt}} + \theta_2 \frac{\sum_{m \in M_{ct}} (Dep_{jmt} + Dep_{amt})}{\sum_{k \in m, m \in M_{ct}} Dep_{kmt}} \tag{2.3}$$

M_{ct} is the set of markets where Bank i and Bank j both operate, or Bank i and Bank a, Bank j's acquirer, both operate at time t. M_{it} is all markets Bank i is in at time t. Dep_{imt} is the total sum of deposits of Bank i in market m at time t. Hence, the term $\frac{\sum_{m \in M_{ct}} Dep_{imt}}{\sum_{m \in M_{it}} Dep_{imt}}$ measures what fraction of Bank i's operation is directly affected by Bank j's failure and acquisition by Bank a. The term $\frac{\sum_{m \in M_{ct}} (Dep_{jmt} + Dep_{amt})}{\sum_{k \in m, m \in M_{ct}} Dep_{kmt}}$ captures the combined dominance of Bank j and its acquirer Bank a in their combined markets. The denominator is the total deposits of all banks in the combined markets of Bank j and Bank a. So the term is essentially measuring the market share of Bank j and Bank a in the markets in which they are present. θ_1 should be significant, since the spillover effect on Bank i should be more pronounced if the affected markets consist of a large part of Bank i's operation. θ_2 should also be significant, since mergers of two more dominant banks in affected markets should impact peer banks more.

For expositional simplicity, I let $exposure_{1ij} = \frac{\sum_{m \in M_{ct}} Dep_{imt}}{\sum_{m \in M_{it}} Dep_{imt}}$, and $exposure_{2ij} = \frac{\sum_{m \in M_{ct}} (Dep_{jmt} + Dep_{amt})}{\sum_{k \in m, m \in M_{ct}} Dep_{kmt}}$. The final regression specification can be written as follows by plugging equation 2.3 back into equation 2.2,

$$\begin{aligned} F_{it} = \alpha + \theta_0 \sum_{j \in P_i} F_{jt} + \theta_1 \sum_{j \in P_i} exposure_{1ij} F_{jt} + +\theta_2 \sum_{j \in P_i} exposure_{2ij} F_{jt} \\ + \sum_{j \in P_i} X_{jt} \gamma + X_{it} \eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it} \end{aligned} \tag{2.4}$$

I call $\sum_{j \in P_i} exposure_{1ij} F_{jt}$ exposure1-weighted failed peers, and $\sum_{j \in P_i} exposure_{2ij} F_{jt}$ exposure2-weighted failed peers.

Table 2.4.3 Columns (1), (2) and (3) show that if an acquirer and an affected bank were competitors before a focal failure, the affected bank's failure probability would be even lower. Table 2.4.3 Columns (4), (5) and (6) provide some weak evidence that if the acquirer is from the same market as the failed bank, the affected bank is less likely to fail. These results offers some clues of the signs of $\theta_1$and θ_2. $Exposure_1$is larger with peer acquirers and with a larger fraction of the affected bank's business in the markets shared with the acquirer. Hence, $\theta_1$is expected to be negative. On the other hand, since Table 2.4.2 shows that on average peer failure leads to lower failure probability for affected banks, and the larger $exposure_2$is, the larger the impact on affected banks should be. Hence, θ_2 is likely to be negative as well.

Table 2.4.3 Column (1) reports the results of the regression. Both θ_1 and θ_2 are significant. Moreover, in fact, the negative θ_1 is consistent with the results in Table 2.4.3. An increase in exposure1-weighted failed peers suggests the affected bank has larger fraction of operation in the markets where there has been a bank consolidation because a healthy bank acquired a failed bank. Hence, the affected banks should receive a larger impact, and thus have even lower failure probability through the potential competition channel. The result that θ_2 is also negative follows from similar logic. Imagine the situation in which the failing bank and the acquiring bank are both very small compared with their competitors in the market. Then, even though their consolidation leads to fewer banks, the effects on market power should be minimal since they did not have much market power in the first place. When the acquiring and failing institutions are large players in their markets, the consolidation of the two should have a large impact on the industrial organization structure, leading to lower failure probability of other banks in these markets.

Columns (2) to (5) of Table 2.4.3 report the results on several operating variables. Column (2) shows that banks with more exposure to a failure and the subsequent acquisition realized higher earnings, consistent with the lower failure probabilities in Column (1). Also consistent with lower failure probabilities, banks with more exposure to the failure and following acquisition have better liquidity, as seen in

Variables	(1) $Fail$	(2) $Earn$	(3) $Capad$	(4) ΔDep	(5) Liq
$exp1 - Failed\,Peers$	-0.0029**	0.0035***	-0.000	0.0130	0.0036***
	(0.001)	(0.000)	(0.001)	(0.011)	(0.001)
$exp2 - Failed\,Peers$	-0.3848***	0.0001	0.0519**	0.5766	0.0476*
	(0.089)	(0.015)	(0.024)	(0.464)	(0.027)
$\#\,Failed\,Peers$	-0.0306***	0.0017***	0.0094***	0.0348***	-0.0036***
	(0.002)	(0.000)	(0.001)	(0.010)	(0.001)
$Controls$	Yes	Yes	Yes	Yes	Yes
$MSA \times Epoch$	Yes	Yes	Yes	Yes	Yes
$Observations$	82,518	82,518	82,518	82,518	82,518
$Adj. - R^2$	0.06	0.04	0.08	0.16	0.14

Table 2.8: **Heterogeneous Spillover Effect with Different Exposure:** This table presents the results of $Y_{it} = \alpha + \theta_0 \sum_{j \in P_i} F_{jt} + \theta_1 \sum_{j \in P_i} exposure_{1ij} F_{jt} + +\theta_2 \sum_{j \in P_i} exposure_{2ij} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it}$. The definitions of $exposure_1$ and $exposure_2$ are in Section 2.4.3. $Controls$ in the table include all X_{it} and X_{jt}, i.e., size, age, peer's mean size and peer's mean age. $Fail$ is an indicator variable of failure in each epoch. $Earn$ is equal to net income divided by total assets. $Capad$ is defined as total equity divided by total assets. ΔDep is the percentage change of total deposits between the year failure happened and one year after that. It is winsorized at the 99th percentile. Liq is liquidity defined as net purchase of fed funds divided by total assets. The sample includes all banks from 2000 to 2014. Failed banks are defined as those appearing on FDIC failed bank list. Standard errors are in parentheses. All standard errors are clustered at bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

Column (5). I did not find significant differential impacts of exposure on deposit growth and capital adequacy.Marginal Acquirers

One concern for reaching the interpretation of heterogeneous spillover effects in the last two sections is that the total number of *Peer Acquirers* and the total number of *Inside Acquirers* can be endogenous, even if the total number of failed peers is instrumented, which casts doubt on the causal interpretation.

The main alternative explanation for the documented results is what I call selection. The acquirers for failed banks are likely to be in better shape than an average bank, possibly because they are experiencing good economic conditions in their markets. Other banks in these markets are also likely to be in better than average conditions. Hence, failure probability will be lower with more peer acquirers. In other words, a bank affected by failed bank transactions with numerous peer acquirers may indicate that the markets it is in are experiencing economic booms. However, under my empirical specification, I argue this is unlikely to be the case since I am controlling for $MSA \times Epoch$ fixed effects. In Appendix 2.D, I characterized the conditions needed for identification of the heterogeneous spillover effects across *Peer* and *Nonpeer Acquirers*, as well as *Inside* and *Outside Acquirers*.

In short, as long as selection affects all related banks the same, identification can be achieved. For *Peer* v.s. *Nonpeer Acquirers*, the heterogeneous spillover effect is identified through comparison between banks affected by the same failures, but with a different competitive relationship with the acquirers. Therefore, the results shown in Table 2.4.3 and Table 2.4.3 are valid since the failed banks and their acquirers never have completely identical sets of peers. For *Inside* v.s. *Outside Acquirers*, the heterogeneous spillover effect can also be identified through a subset of banks affected by peer failures, using a Regression Discontinuity Design (RDD) approach.

Here I explain the identification of heterogeneous spillover effect across *Inside* and *Outside Acquirers*. The more formal and complete demonstration can be found in Appendix 2.D. In my analysis, I exploited the bidding information on the auctions for failed banks, first identifying the failures in which one type of acquirer marginally wins over the other type. For example, in one failure, an $Inside\,Acquirer$ won the auction over an $Outside\,Acquirer$, but the difference in their bids was less than 1% of the failed bank's asset value. I argue that in these cases, some exogenous force determines the observed type of the winner, since the winner and the second place have very close valuations. The concern here is that the spread in the top two bids can affect the outcome variable in a nonlinear way. If unaccounted for, this nonlinear effect would be falsely attributed to the spillover effect. For two banks affected by inside and outside acquirers respectively, if the spreads in the top two bids are narrow enough, I can argue the nonlinear effect of these spreads on the outcome variable is sufficiently close, assuming the effect is continuous. Therefore, by looking at banks affected by peer failures whose auctions feature a narrow spread between the top two bids, I can identify the heterogeneous spillover effects across $Inside\,Acquirers$ and $Outside\,Acquirers$, through respectively labeled $Mariginal\,Inside\,Acquirer$ and $Marginal\,Outside\,Acquirers$.

Precisely, the acquirer of a failed peer is defined as a $Marginal\,Inside\,Acquirer$ under the following three conditions: First, the winner of the auction for that failed peer has to be an $Inside\,Acquirer$. For example, when looking at Bank B, a bank affected by its peer, Bank A's, failure, the acquirer Bank C has to be a peer to Bank A. In this case, Bank C is considered an $Inside\,Acquirer$. Second, the second highest bid has to be by an $Outside\,Acquirer$. Using the same example, if Bank D takes the second place in the auction, then Bank D has to be an $Outside\,Acquirer$. In other words, Bank D cannot be a peer to the failed Bank A. Third, the difference between the top two bids has to be less than 1% of the target's asset value. Again, with the same example, if Bank A has a $100 million asset value, then the difference between the bids of Bank C and Bank D has to be less than 1$ million. If and only if all three conditions above are satisfied, the acquirer, Bank C in the example, is defined as a $Marginal\,Inside\,Acquirer$.

To implement this RDD-like idea, I first needed to extract the banks only affected by $Marginal\,Inside\,Acquirers$ and $Marginal\,Outside\,Acquirers$ from the full sample used for previous analyses. This procedure significantly reduced the total number of observations in the sample. Hence, the numerical problem due to the large number of $MSA \times Epoch$ dummies and a small sample arose, as discussed above in Section 2.4.3. I adopted the same method used in Section 2.4.3 to compress the dimension of the dummy variables. Then I estimated the models before using the subsample of banks only affected by marginal acquirers,

Table 2.4.3 reports the effects of$Mariginal\,Inside\,Acquirers$ v.s. $Mariginal\,Outside\,Acquirers$. The results are very interesting in that they are drastically different from the results in Table 2.4.3. When only failures for which $Inside\,Acquirers$ happened to be the winners are considered, the results suggest no significant difference from the failures with $Outside\,Acquirers$ in terms of effects on the failure probability of affected banks. In contrast with the results in Table 2.4.3, I can also conclude there exists a significant selection of acquirer types in the failed bank auctions: $Inside\,Acquirers$ tend to have a better assessment of the prospects of a focal failed bank and the market it is in, thus winning auctions with a better outlook than average. The selection effect is so strong that $Inside\,Acquirers$ predict a lower probability of failure as reported in Table 2.4.3 Column (4), even though the causal effect, estimated with $Marginal\,Inside\,Acquirers$, is insignificant. The results in Table 2.4.3, Column (4), seem to suggest that the FDIC should avoid $Outside\,Acquirers$ and favor $Inside\,Acquirers$ since the latter predicts lower failure probability. However, in fact, the FDIC should no particular type of acquirers because $Outside\,Acquirers$ and $Inside\,Acquirers$ are fairly similar in terms of their causal effects on the performance and failure probabilities of other banks. Columns (2) to (5) in Table 2.4.3 provide

Variables	(1) $Fail$	(2) $Earn$	(3) $Capad$	(4) ΔDep	(5) Liq
$\# Marginal\, Inside\, Acquirers$	-0.0017	-0.0015	-0.0044	0.0202	0.0008
	(0.007)	(0.001)	(0.003)	(0.069)	(0.003)
$\# Marginal\, Outside\, Acquirers$	0.0127	-0.0098**	-0.0146**	-0.0534	0.0116**
	(0.021)	(0.004)	(0.006)	(0.127)	(0.005)
$Controls$	Yes	Yes	Yes	Yes	Yes
$Location \times Epoch$	Yes	Yes	Yes	Yes	Yes
$Observations$	55,969	55,969	55,969	55,969	55,969
$Adj. - R^2$	0.01	0.03	0.06	0.14	0.13

Table 2.9: **Heterogeneous Spillover Effects of Peer Bank Failures**: This table presents the results of the regression $Y_{it} = \alpha + \beta_1 \sum_{j \in P_i} Inside_{jt} F_{jt} + \beta_2 \sum_{j \in P_i} Outside_{jt} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{l=1}^{25} \delta_{lt} L_{ilt} + \epsilon_{it}$ on a subsample of banks only affected by peer failures whose acquirers marginally outbid the second highest bidder, and the top two bidders differ in their competitive relationships with the failed bank. Y_{it} is an outcome variable of bank i at epoch t . P_{it} is the set of all banks that are peers of bank i. X_{it} is a vector of control variables. $Controls$ in the table include all X_{it} and X_{jt}, i.e., size, age, peer's mean size and peer's mean age. L_{ilt} is the lth element in the encoding of i's MSA locations at epoch t. $Inside_{jt}$ is an indicator variable equal to 1 if bank j is acquired by a peer bank after failure at epoch t, and that acquirer marginally won a bidder that is not a peer to bank j. $Earn$ is equal to net income divided by total assets. $Capad$ is defined as total equity divided by total assets. ΔDep is the percentage change of total deposits between the year failure happened and one year after that. It is winsorized at the 99th percentile. Liq is liquidity defined as net purchase of fed funds divided by total assets. Failed banks are defined as those appearing on the FDIC failed bank list. Standard errors are in parentheses. All standard errors are clustered at bank level. *, **, *** denote significance at 10%, 5%, 1% respectively.

some weak evidence that *Marginal Outside Acquirers* tends to cause deterioration in the performance of affected banks. However, the effect is not strong enough to manifest as a higher failure probability.

2.5 Conclusion

This paper shows that bank failures on average lead to a lower failure probability of affected banks competing with the failed banks. However, both the competitive relationship between the affected banks and the acquirers of the failed banks, and the competitive relationship between the failed banks and their acquirers, play crucial roles in determining the actual spillover effects on individual affected banks. I find bank failures lead to lower failure probability among banks that also compete with the acquirer, and a higher failure probability among banks that do no compete with the acquirer. I argue this outcome is consistent with the existence of a competition channel. From the perspective of an affected bank that is also a competitor of the acquirer, banks in its market are consolidated as the result of the acquirer's purchasing the failed bank. The consolidation raises market power for these affected banks, resulting in higher profit and lower failure probability. Reduction in the supply of mortgage loans among these banks is further evidence for the existence of a competition channel. One central objective of the FDIC when resolving failed banks is to minimize direct monetary cost, as evidenced by the Least Cost Resolution policy. Without taking a stand on whether or not the FDIC is actually following this policy, the results in this paper reveal the potential wedge between the minimal cost option in one bank failure case and the minimal cost option over multiple interdependent bank failures, caused by the existence of the competitive spillover effect. My findings suggest that the FDIC should take into account the consequences on the competitive relationship among banks of all resolution options, to ensure more cost efficient resolution of failed banks over time.

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Appendix

2.A Interpretation of Spillover Effect β

The baseline structural equation 2.1 is as follows

$$F_{it} = \alpha + \beta \sum_{j \in P_i} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it} \tag{2.5}$$

For expositional ease, I leave out the time index t. Consider a bank i, let Y_i be the average failure rate of its peers, which is given by

$$Y_i = \frac{\sum_{j \in P_i} F_j}{\|P_i\|}$$

where P_i is the set of bank i's peers, and $\|P_i\|$ is the total number of peers bank i has.

The impact of bank i's failure on the average failure rate of its peers, Y_i, is then

$$\begin{aligned}
\frac{\partial Y_i}{\partial F_i} &= \frac{1}{\|P_i\|} \sum_{j \in P_i} \frac{\partial F_j}{\partial F_i} \\
&= \frac{1}{\|P_i\|} \sum_{j \in P_i} \left[\frac{\partial}{\partial F_i} \left(\alpha + \beta \sum_{k \in P_j} F_k + \sum_{k \in P_j} X_k \gamma + X_j \eta + \sum_{m \in M_j} \mu_m + \epsilon_j \right) \right] \\
&= \frac{1}{\|P_i\|} \sum_{j \in P_i} \left[\frac{\partial}{\partial F_i} \left(\beta \sum_{k \in P_j} F_k \right) \right]
\end{aligned}$$

For any $j \in P_i$, we must have $i \in P_j$. Hence, we can further get,

$$\begin{aligned}\frac{\partial Y_i}{\partial F_i} &= \frac{\beta}{\|P_i\|} \sum_{j \in P_i} \left[\frac{\partial}{\partial F_i} \left(\sum_{k \in P_j} F_k \right) \right] \\ &= \frac{\beta}{\|P_i\|} \sum_{j \in P_i} 1 \\ &= \beta\end{aligned}$$

Therefore, we can interpret the coefficient β as the impact of one bank failure on the average failure probability of all its peers.

2.B Learn the Epochs of Failures

The data observed are official closure dates of all I failures, denoted by $\{t_i\}_{i=1,...,I}$. Suppose there are N epochs of failures in total, denoted by $n = 1, ..., N$, and every failure is associated with one and only one of these epochs. Hence, each failure is characterized by the tuple $\{t_i, e_i\}$, where $e_i \in \{1, ..., N\}$ is the unobservable, or latent, epoch associated with failure i. Each epoch has 2 corresponding characteristics, $\theta_n = \{\bar{t_n}, \sigma_n^2\}$, which are the mean date of that epoch, and the variance of failure dates of that epoch. Adopting the Gaussian Mixture Model (GMM), the data generating process of these closure dates are given by the following process:

1. For each failure i, draw an epoch $e_i \in \{1, ..., N\}$ from a distribution of epochs, with $Pr(e_i = n) = \pi_n$, and $\sum_{n=1}^{N} \pi_n = 1$.

2. Draw the closure date of failure i, conditional on the epoch assignment e_i, according to the Gaussian Distribution $t_i \sim N(\bar{t}_{e_i}, \sigma_{e_i}^2)$.

The objective of a learning algorithm for this GMM is to learn all parameters $\{\pi_n, \bar{t_n}, \sigma_n^2\}_{n=1,...,N}$ and latent epochs $\{e_i\}_{i=1,...,I}$, with data $\{t_i\}_{i=1,...,I}$ and prespecified number of epochs

N. This is done using an Expectation Maximization (EM) algorithm by choosing the parameters that maximize the expected likelihood of the joint distribution. Concretely, the joint expected likelihood is given by

$$p\left(\{t_i\}_{i=1,\ldots,I} \middle| \{\pi_n, \bar{t_n}, \sigma_n^2\}_{n=1,\ldots,N}\right) = \prod_{i=1}^{I} \sum_{n=1}^{N} \pi_n N\left(t_i \middle| \bar{t_n}, \sigma_n^2\right)$$

After training with the EM algorithm is completed, for any closure time t, we can use the learned parameters to compute the likelihood of epoch assignment

$$L\left(e = n|t\right) = \frac{\pi_n N\left(t|\,\bar{t_n}, \sigma_n^2\right)}{\sum_{n=1}^{N} \pi_n N\left(t|\,\bar{t_n}, \sigma_n^2\right)}$$

Then the closure time t will be assigned to epoch n_t that maximizes the likelihood above.

2.C Compression of MSA dummies

The objective here is find a lower dimensional representation of MSA vectors of each bank. Denote the MSA matrix as M, and the lower dimensional representation as E. M has dimension $N \times K$, where N is the number of banks, and K is the number of MSAs, which is 382 in my sample. E has dimension $N \times k$, where $k < K$ is the dimension for the encoding. Let m be a row of M, and e be a row of E. So m is the MSA vector for one bank, and e is the encoding vector for one bank. The compression is a mapping $f : \{0, 1\}^K \mapsto \mathbb{R}^k$, with

$$e = f\left(m\right)$$

Let $h : \mathbb{R}^k \mapsto [0, 1]^K$ be the decoding function, we have

$$\hat{m} = h\left(e\right)$$

here $\hat{m}$ can be thought of as a reconstruction of m given encoding e.

Recall the regression equation

$$Y_{it} = \alpha + \beta \sum_{j \in P_i} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it}$$

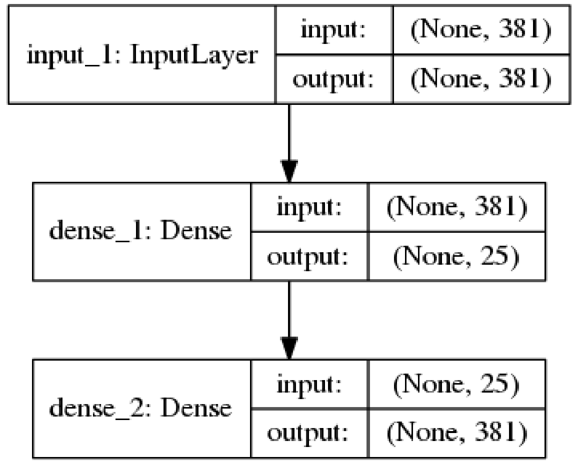
The $MSA \times Epoch$ fixed effects can be rewritten in vector form

$$\begin{aligned} \sum_{m \in M_{it}} \mu_{mt} &= \mu_t^{'} m_i \\ &= \mu_t^{'} \hat{m}_i + \epsilon \end{aligned}$$

We can see here the compression will introduce noise ϵ into the variables, since the construction is not perfect.

The goal then is to find mapping f, h which minimizes the reconstruction error, for a given number of dimension k.

In this paper, I utilize the so-called autoencoder from machine learning literature. An autoencoder is essentially a fully connected neural network with one hidden layer, an input layer, and an output layer. The hidden layer can be called an encoder, and the output layer can be called a decoder. The input layer has K units, which takes m as the input. The hidden layer, or the encoder, then transforms m into e using mapping f. It has K input dimensions and k output dimensions. Then the output layer, or the decoding layer transforms e into $\hat{m}$ using mapping h. It has k input dimensions and K output dimensions. The complete architecture of the network is shown below. The learning algorithm is trying to find f and h, such that the reconstruction error is minimized.



In practice, I choose $k = 25$, which is sufficient for the reconstruction to explain over 80% of variation in M for any year. I need around 90 principal components to achieve similar performance using Principal Component Analysis. To speed up training, I use rectified linear (ReLU) activation function for the encoder, and I use sigmoid activation function for the decoder so that all elements of the reconstruction is between 0 and 1. The objective function the learning algorithm is minimizing is binary cross-entropy function where the loss for each observation is given by

$$L(m, \hat{m}) = -\frac{1}{K}\sum_{k=1}^{K}\left[m_k \log \hat{m}_k + (1 - m_k)\log(1 - \hat{m}_k)\right]$$

Finally, I use Adam optimizer to minimize the objective function above, which is frequently used for this type of objective functions.

2.D Identification of Heterogeneous Spillover Effects

Recall the baseline model

$$F_{it} = \alpha + \beta \sum_{j \in P_i} F_{jt} + \sum_{j \in P_i} X_{jt}\gamma + X_{it}\eta + \sum_{m \in M_{it}} \mu_{mt} + \epsilon_{it}$$

For notation simplicity, consider another similar model

$$Y_i = \alpha + \beta Z_i + u_i$$

where Y_i can be thought of as the failure indicator in the baseline model, and Z_i can be thought of as the total number of failed peers. This simplified model is sufficient in demonstrating the potential endogeneity problem when looking at heterogeneous spillover effect.

Assume $E[\epsilon_i|Z_i] = 0$, then β is identified. One can think of Z_i as the instrumented number of failed peers. Here β can be thought of as the average spillover effect across all acquirer types.

Now consider the following model to be the true data generating process for Y_i,

$$Y_i = \alpha + \beta_1 Z_{1i} + \beta_2 Z_{2i} + f(W) + \epsilon_i \tag{2.6}$$

where Z_{1i} is the total number of failed peers acquired by Type 1 acquirers and Z_{2i} is the total number of failed peers acquired by Type 2 acquirers. Hence, $Z_{1i}+Z_{2i} = Z_i$. W is a variable correlated with Z_{1i} and Z_{2i}. $f(\cdot)$ is some continuous function. Without loss of generality, suppose $E[f(W)] = 0$. Therefore, we must have $E[f(W)|Z_{1i}, Z_{2i}] \neq 0$. We also need $E[f(W)|Z_i] = 0$. Now it is easy to see if we run the regression

$$Y_i = \alpha + \beta_1 Z_{1i} + \beta_2 Z_{2i} + u_i$$

β_1 and β_2 cannot be consistently estimated because $E[u_i|Z_{1i}, Z_{2i}] = E[f(W)|Z_{1i}, Z_{2i}] \neq 0$. However, if we run the regression

$$Y_i = \alpha + \beta Z_i + u_i,$$

the average spillover effect can be consistently estimated because $E[u_i|Z_{1i}+Z_{2i}] = 0$. Here we see the situation where the average spillover effect can be identified but heterogeneous spillover effect cannot. The basic idea is that even if the total number of failed peers is exogenous, the composition of acquirer types may still be endogenous.

To better illustrate the idea, consider the following example where $f(W) = W$, $Z_{1i} = \frac{1}{2}(Z_i + W)$, $Z_{2i} = \frac{1}{2}(Z_i - W)$. So we have $Z_{1i} + Z_{2i} = Z_i$. We can immediately have $E[W|Z_i] = 0$ following the assumption $E[f(W)|Z_i] = 0$. At the same time, we also have $E[W|Z_{1i}, Z_{2i}] = Z_{1i} - Z_{2i} \neq 0$ in general.

Next I will show how to identify the heterogeneous spillover effects of peer v.s. nonpeer acquirers, and inside v.s. outside acquirers.

First consider the heterogeneous spillover effect between peer and nonpeer acquirers. Let U be the set of failed banks. Let W_u be the variable correlated with both the identity of the acquirer of failed bank u and the outcome variable Y_i for all $i \in P_u$. I will show the heterogeneous spillover effect is identified by looking at peers of the acquirer and nonpeers of the acquirer, that are affected by the failed bank u. Concretely, for a bank $i \in P_u$,

$$Y_i = \alpha + \beta_1 D_{iu} + \beta_2(1 - D_{iu}) + f_i(W_u) + \epsilon_i$$

where $D_{iu} = 1$, if $i \in P_k$, and k is the acquirer of failed bank u.

Now assume the following

$$f_i(W_u) = h(W_u) + e_i$$

where $Cov(e_i, e_j) = 0$ for $i \neq j$. This assumption is saying the effect of W_u on affected banks has a common and idiosyncratic components, which are additively separable.

Now for banks $i, j \in P_u$, and $i \in P_k, j \notin P_k$, we have

$$Y_i = \alpha + \beta_1 + h(W_u) + e_i + \epsilon_i$$

$$Y_j = \alpha + \beta_2 + h(W_u) + e_j + \epsilon_j$$

The heterogeneous spillover effect is identified because

$$E\left[Y_j - Y_i \middle| D_{iu}, D_{ju}\right] = \beta_2 - \beta_1$$

To sum up, the peer v.s. nonpeer heterogeneous spillover effect is identified through banks that are affected by the same set of failures, but are peers and nonpeers of the acquirers.

Then consider the heterogeneous spillover effect between inside and outside acquirers. Following the same framework, for any bank i affected by failure u, we have

$$Y_i = \alpha + \beta_1 D_u + \beta_2(1 - D_u) + h(W_u) + e_i + \epsilon_i$$

where $D_k = 1$, if $i \in k$. Bank k is the acquirer of bank u.

Notice that D_k does not vary across i, for all $i \in P_u$. Here we need additional assumption, and adopt a Regression Discontinuity Design approach to identify the heterogeneous spillover effect.

Let $W_u = B_{u,inside} - B_{u,outside}$, where $B_{u,inside}$ is the highest bid of an inside bidder. Then it is clear that $D_k = 1\left\{W_u \geq 0\right\}$. Since $h(W_u)$ is continuous, we have $h(-\varepsilon) \approx h(\varepsilon)$ for ε close to 0. Then for banks $i \in P_u, j \in P_s$, and bank u and s are both failed, i.e.$u, s \in U$. When $0 < W_u < \varepsilon$ and $-\varepsilon < W_s < 0$, we have

$$Y_i = \alpha + \beta_1 + h(W_u) + e_i + \epsilon_i$$

$$Y_j = \alpha + \beta_2 + h(W_s) + e_j + \epsilon_j$$

Thus

$$E\left[Y_j - Y_i \middle| D_u, D_s\right] = \beta_2 - \beta_1$$

Next I will show this method can be extended to banks affected by multiple peer failures, which all feature narrow spreads in top 2 bids.

Again, consider two banks

$$Y_i = \alpha + \beta_1 \sum_{u \in P_i} D_u + \beta_2 \left(1 - \sum_{u \in P_i} D_u\right) + \sum_{u \in P_i} h\left(W_u\right) + \sum_{u \in P_i} e_u + \epsilon_i$$
$$Y_j = \alpha + \beta_1 \sum_{u \in P_j} D_u + \beta_2 \left(1 - \sum_{u \in P_j} D_u\right) + \sum_{u \in P_j} h\left(W_u\right) + \sum_{u \in P_j} e_u + \epsilon_i$$

When $P_i \neq P_j$, but $\|P_i\| = \|P_j\|$, since $W_u \in (-\varepsilon, \varepsilon)$, we know $\sum_{u \in P_i} h\left(W_u\right) \approx \sum_{u \in P_j} h\left(W_u\right)$, hence, we can get

$$E\left[Y_j - Y_i \middle| \left\{D_u\right\}_{u \in P_i}, \left\{D_s\right\}_{s \in P_j}\right] = \left(\beta_1 - \beta_2\right)\left(\sum_{u \in P_j} D_u - \sum_{u \in P_i} D_u\right)$$

Then the heterogeneous spillover effect can be obtained

$$\beta_1 - \beta_2 = \frac{E\left[Y_j - Y_i \middle| \left\{D_u\right\}_{u \in P_i}, \left\{D_s\right\}_{s \in P_j}\right]}{\sum_{u \in P_j} D_u - \sum_{u \in P_i} D_u}$$

As long as we have two banks i and j with different composition of $Inside$ and $Outside\ Acquirers$ among their failed peers, the heterogeneous spillover effect can be estimated by the sample analog of the expression above.

To sum up, the heterogeneous spillover effects are identified through failures where an inside bidder narrowly outbid an outside bidder, and an outside bidder narrowly outbid an inside bidder.

It is easy to see the identification above will work if $f_i(W_u) = h(W_u) + g(X_i) + e_i$, and X_i are some observable characteristics of bank i, by controlling for these variables.

Specifically, in the implementation of this paper, I control for size, age, and the markets that the bank is operating in.

Chapter 3

Heterogeneous Effects of Bank Consolidations in Local Markets: Evidence from Branch Level Data

3.1 Introduction

Researchers and policy makers have long recognized bank consolidation can be a double edged sword in terms of its welfare implications. On the one hand, bank mergers and acquisitions (M&As) may lead to efficiency gain. For example, TV commercials that advertise a bank's services is more cost efficient for a larger consolidated bank. In fact, bank consolidation will benefit from economy of scale due to the existence of all kinds of fixed cost. However, on the other hand, bank consolidations also have competition effects granting higher market power to the bank, which potentially allows the bank to extract more rent from consumers, and can even lead to lower social welfare. The benefit from efficiency gain may be fully retained by the banks, but never gets passed onto consumers. Consumers may even be harmed due to the increased market power of the banks. Being able to empirically identify *efficiency effects* and *competition effects* is the first step of analyzing the costs and benefits of bank consolidations, as well as any policy that may potentially affect bank consolidation activities. It will be ideal if one can exploit the *efficiency effects* but limit the *competition effects*, so that consumers can benefit from bank M&As. It is challenging to simultaneously identify these two effects because *efficiency* and *competition effects* are confounding each other in generating almost all outcomes of bank consolidations that econometricians can observe.

This paper contributes to existing literature on this topic in the following aspects. Firstly, this paper proposes a new experiment design exploiting branch level variation during bank M&As, which allows for simultaneous identification of *efficiency effects* and *competition effects*. The results shed light on the within-bank cross-branch and cross-region differential impact of bank consolidations. Secondly, this paper explores the implications of bank mergers on mortgage loans borrowers, an important group of borrowers that are underinvestigated in previous literature. Thirdly, this paper explores the differential impact of bank consolidations across different groups of borrowers and different economic conditions. In particular, this paper provides a more complete picture of consequences of government-assisted mergers and mergers that happen in economic downturns.

The identification strategy in this paper can cleanly identify the *competition effects*, even with *efficiency effects* potentially confounding the final results we observe. The main idea is that when two banks with overlapping branch networks merge, the change in competition for each branch varies depending on how close the previously competing branches are. The a difference-in-differences setup can be used to identify the cross-branch differential impact with appropriate controls. Take PNC Bank acquiring National City Bank in 2008 for example. Prior to the merger, Pittsburgh was one of the markets which both PNC and National City had major presence in, while PNC does not have many branches in the Midwest. It is intuitive that the PNC branches in Pittsburgh experienced a significant decrease in competition from National City branches in the same city, while the newly acquired branches in the Midwest, and existing PNC branches located in areas absent of National City presence, experienced little change in local competitive conditions. One can then infer the *competition effects* from this acquisition by looking at relevant changes for the branches in Pittsburgh, relative to the branches where there was no National City nearby before the acquisition.

I implement the identification method on a data set of branch level deposits, and a data set of individual mortgage loan applications, using more than 300 bank mergers and acquisitions as the experiment. The first main finding of this paper is that *efficiency effects* lead to an increase in deposit growth for branches involved in mergers and acquisitions by 2.4 percentage points annually, relative to branches never participated in a merger. On the other hand, *competition effects* push down the deposit growth for the branches which gained market power more by 3.5 percentage points, compared to branches with little change in market power but also participated in the same mergers.

To better understand the *competition effects* on bank consolidations, the second main finding shows in census tracts with larger decline in bank competition due to the M&As, there are larger increase in the denial rates of mortgage loan applications. The two findings together suggest that banks can clearly take advantage of the within-bank variation in market power gain following the mergers. Specifically, they limit the supply of mortgage loans in regions where they gain more market power. As a costly input for the branches in these regions, they will also lower their demand for deposits, as documented in the first finding.

The third main finding looks at the cross-section heterogeneity of the effects. M&As with government assistance generate quantitatively more *efficiency effects* for the banks involved in terms of deposit growth. Transactions that happen during recessions depict insignificant *efficiency effects*, but *competition effects* are stronger than normal times. More interestingly, across different groups of borrowers, I find that low-income borrowers are especially harmed, facing higher denial rates in particular even after controlling for loan characteristics, due to the increase in market power of the merged banks in local markets. The surge in denial rates for these low-income borrowers is more pronounced for government-assisted mergers, and mergers during recessions. This finding cautions the government when evaluating the consequences of government-assisted M&As involving failed banks.

3.1.1 Related Literature

This paper is related to the literature attempting to assess the overall implications of bank consolidations on banks as well as consumers.

Researches in 1990s have provided evidence that banks in more concentrated markets tend to charge higher rates on loans, while pay lower rates on deposits. Berger and Hannan (1989) presents one of the earliest evidence that banks in more concentrated markets pay significantly less interest rates on several deposit types, implying banks may be exercising their monopsonistic market power when attracting deposits. However, researches only find mixed evidence that the efficiency and market power gains due to mergers and acquisitions can translate into better operating performance and stock market returns. Houston and Ryngaert (1994) examines mergers and acquisitions between 1985 and 1991, and concludes that measured by abnormal returns, the transactions only show slightly positive but statistically insignificant gains. On the contrary, Cornett and Tehranian (1992) finds large banks involved in mergers and acquisitions demonstrate improvements in attracting loans and deposits, as well as employee productivity. These gains are indeed incorporated into their stock prices by the market. Given these mixed results, later researches tend to try to identify the determinants of merger gain magnitude and its source. Palia (1993) identifies several determinants of bank merger gains including managerial, regulatory and financial factors. Houston et al. (2001) finds that even though it is hard to find conclusive evidence on overall value creation of mergers and acquisitions, the authors are able to provide evidence that larger transactions are more likely to be value creating for the participants, and the gain mainly comes from cost savings. The results highlight the potential social cost of bank consolidation, and the fact that borrowers and depositors are paying the cost.

From a theoretical point of view, more competition among banks may or may not be beneficial to depositors and/or borrowers. Klein (1971) offers one of the earlier theoretical predictions that less competition among banks leads to higher borrowing rates, and less supply of credit. But the results do not hold when information asymmetry between banks and borrowers comes into play, as pointed out by Marquez (2002) and Petersen and Rajan (1995). Empirical researchers adopt various quasi-natural experiment settings, trying to identify the consequences of changes in bank competition. Small firm financing has drawn quite some attention in this line of research. Berger et al. (1998) finds consolidated banks do reduce lending to small firms, but the effects are mostly offset by other banks in the same markets. Zarutskie (2006) provides evidence that new firms borrow less external financing and invest less after the deregulation, by exploiting Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, which is considered to lead to an increase in competitiveness. Cetorelli and Strahan (2006) presents evidence that new entrants of nonfinancial sectors are more external credit constrained in the markets where banks are more concentrated. Dinc (2000) shows that higher competition among banks incentivizes them to commit to lend to their relationship borrowers, even with dropping credit quality. Rice and Strahan (2010) presents evidence that the small firms in states more open to branching are borrowing at lower rates.

A number of studies has also examines the impact of bank consolidations on consumers. Focarelli and Panetta (2003) separately identifies the *competition and efficiency effects* of bank consolidations using detailed Italian data, and concludes that in-market consolidations lead to a lower deposit rates in the short run. But in the long run, *efficiency effects* will dominate, resulting in higher deposit rates, which is beneficial to the depositors. Garmaise and Moskowitz (2006) finds borrowing rates are higher in the neighborhood with more bank mergers. Moreover, they find these neighborhoods will also see an increase in property crime following the mergers.

The rest of this paper will be organized as follows. Section 3.2 will layout my complete identification, and the procedures used to process the data and construct the main sample. Section 3.3 will present the results and discuss their implications. Section 3.3 will conclude.

3.2 Empirical Strategy

3.2.1 Data

The data used in this research come from four main sources. Annual Summary of Deposit (SOD) summary survey data is available on Federal Deposit Insurance Corporation website, it provides total sum of deposits for all branch offices in the US of all banks, which is one of the main dependent variables, and more importantly, physical locations of each branches in forms of addresses and geographical coordinates of most branches. Each branch is uniquely identified by this physical location, no matter who owns that branch. It also comes with some financial information of the institution and/or bank holding company owning each branch from Call Reports. The geographical coordinates are essential to compute the physical distance between branches, which further allows me to identify the branches experiencing large changes in competition following M&As. The SOD data are available from 1994.

Bank mergers and acquisitions data is maintained by Federal Reserve Bank of Chicago, which contains identifiers for surviving and nonsurviving banks, dates of the events from as early as 1976. The merger cases that end up in my final sample are all from this data set.

I use Home Mortgage Disclosure Act (HMDA) to extract loan application information including the banks' acts on each application, the census tract of the property, income of the borrower, amount of the loan, and various other loan characteristics. This data set is used to identify the impact of bank consolidations on mortgage loan borrowers.

Finally, I need to obtain the geographical coordinates of the census tract in order to match the branch locations to census tracts. I obtain geographical coordinates of the interior points of census tracts defined in different census waves from US Census Bureau website.

3.2.2 Identification Strategy

This paper exploits within-bank cross-branch variation in competition changes during mergers and acquisitions to identify the *competition* and *efficiency effects* of these events. I implement the strategy by the following regression:

$$y_{ict} = \alpha_0 + \alpha_1 Close_i \times Post_t + \alpha_2 Merge_i \times Post_t + \mu_i + \nu_c \times t + \epsilon_{ict} \tag{3.1}$$

Here i indexes the branches, c indexes the county in which the branch is located, t indexes time. $Post_t$ is a dummy variable equal to one after the mergers and acquisitions. $Close_i$ is a dummy variable equal to one if there exists one or more branches of the merger counterpart bank in proximity. $Merge_i$ is a dummy variable equal to one if branch i has ever been involved in a merger. μ_i extracts branch level fixed effect, $\nu_c \times t$ extracts all variations on county-year level. For this specification, a stacked branch-year panel is used to explore the implications of bank consolidations on deposit growth, which is a main dependent variable used in the regression.

To demonstrate how this specification can identify *efficiency* and *competition effects*, I will start from the intuition of the simplest regression and illustrate the necessity of all the components in this specification. First, let us imagine the most naive regression specification,

$$y_{ict} = \alpha_0 + \alpha_1 Close_i \times Post_t + \epsilon_{ict}$$

This regression is in the form of a Difference-in-Differences design, where $Close_i$ identifies the treatment and control group. Branches have $Close_i = 1$ when there exists branches nearby owned by the merger counterpart institution. α_1 extracts the difference in changes in the dependent variable between the branches with previously competing branches nearby and all other branches including branches of the two parties in the merger as well as branches of other banks in the same neighborhood. However, α_1 cannot be interpreted as *competition effects* yet, it is most likely confounded by *efficiency effects*. Imagine the case where there is no *competition effects* in a merger, all changes in the dependent variable, say deposit growth are due to *efficiency effects*. In this case, the branches of the two banks involved in the merger will experience similar cost saving, so we expect to see changes in deposit growth across all these branches. This effect will be picked up by α_1, but it is not the *competition effect* that I try to identify, and in fact it does not even vary with the changes in local competition due to the merger. This problem highlights the challenge of identifying both effects while one can only observe the net outcome measured by the dependent variable.

The full specification in (3.1) is designed to address the concern above, along with other potential challenges. In short, this specification looks at the changes in the dependent variable in all the branches of the two merging banks with opponent branches nearby, while using the branches of the same banks but without opponent branches nearby as controls.

I argue that α_2 captures the *efficiency effects* under the assumption that branches of the merged bank enjoy similar, if not exactly the same, benefit from the *efficiency effects* of the merger. This assumption is reasonable because *efficiency effects* of bank mergers and acquisitions usually come at the institution level, including fixed cost saving, geographical diversification, etc.. Even if the assumption does not hold at its face value, one can still think of α_2 capturing the *average efficiency effects*. So one can still credibly interpret α_1 as the *competition effects* since $Close_i$ captures the difference in changes in competitiveness across branches.

Another concern of investigating consequences of bank mergers and acquisitions appears when there are government assisted transactions in the sample. In these cases, there are usually failing banks involved. Suppose a financially healthy bank acquires a failing bank during a financial crisis. One can imagine the branches of the failing bank demonstrate a mean-reversion-like behavior in terms of performance after the acquisition. Depositors worry about the safety of the deposits when the bank is failing so they withdraw their deposits. Under extreme scenarios, these banks may be subject to runs, which will deplete the deposits in the branches. After the acquisition, depositor confidence will be rebuilt as the branches of the failing bank will be likely rebranded under the acquirer, a much financially healthier bank, and start to deposit in these branches again. This effect is in fact more of a result from the financial and managerial aid provided by the acquirer, instead of either *efficiency* or *competition effects*. α_2 will take out this effect too, since if there is such mean-reversion-like behavior, we should observe similar pattern in all the branches of the failing bank.

α_1 still identifies the extra changes in the dependent variable that varies with local competitive condition.

Last but not least, I also include branch fixed effect μ_i which controls for all time-invariant branch level characteristics. County-year fixed effect $\nu_c \times t$ controls for all local economic condition changes at county level.

A similar specification is used when this identification strategy is used on the HMDA data, which contains repeated cross sections of loan level information Since the finest geographical identifier I can observe with HMDA data is census tract, I need to redefine the treatment variables at census tract level. The regression is as follows,

$$y_{ijct} = \alpha_0 + \alpha_1 Close_i \times Post_t + \alpha_2 Merge_i \times Post_t + X_i + \mu_j + \nu_c \times t + \epsilon_{ijct} \quad (3.2)$$

Here, i indexes loans, j indexes census tracts, c indexes counties, and t indexes years as before. Notice that $Close$ and $Merge$ are still defined on the branch level as before. $\alpha_1$and α_2 will be identified from the cross-region differences in proportion of branches that have opponent branches nearby, and branches that are involved in M&As. The details of constructing the sample needed for this regression is described in Section 3.2.3. X_i are loan level controls, which may include applicant income, loan amount, loan type and loan purpose. The main dependent variable here is the dummy for loan application denial.

I further explore the cross-section heterogeneity in the *competition* and *efficiency effects* across high- and low-income mortgage loan applicants, as well as acquiring and target institutions by interacting corresponding dummies with $Close \times Post$ and $Merge \times Post$.

3.2.3 Sample Construction

I start with the bank M&As data set from Chicago Fed. I require the M&As happen between two different bank holding companies, which is more relevant to study *competition effects.* For the mergers of banks owned by the same bank holding company, there may not even be any change in local competition conditions. The information on if a certain transaction has government assistance involved is also extracted from this data set. Since the Summary of Deposits data with branch level information are only available after 1994, I will only select the M&As that happen after that.

Then I identify the branches of the banks involving in the mergers and acquisitions from the Summary of Deposits data set from FDIC. Only brick-and-mortar branches are included. I define the variable $Close_i$ which identifies the treatment group in the following way. First I drop all branches with geographical coordinates missing[1], so I can compute pairwise spherical distance from any one branch of surviving bank to any one branch of the nonsurviving bank. If there is at least one opponent branch located within x kilometers from that branch 1 year before the merger, then that branch will be defined as $Close_i = 1$. I set $x = 10km$ for the results presented in all the tables, unless otherwise noted. I will also conduct extensive robustness checks with different values of x. After these branches are identified, I include two types of branches in the same county as control group: all branches of the two banks involved in this merger, and all branches of the banks that have never been in a merger. I collect all the information of these branches up to 3 years before the transaction, and 3 years after. This forms my main branch-year panel. At branch level, the main dependent variable is deposit growth, which is the percentage growth of sum of deposits in each branch from last year. This variable is winsorized at 2.5 and 97.5 percentiles.

[1] I use OpenStreetMap API to geocode the addresses of some branches, allowing me to recover more than half of the branches with coordinates missing in the raw data.

Recall that my identification strategy requires that for any branch with $Close_i = 1$, there must be at least one branch of the same bank with $Close_i = 0$. So the latter type of branches can be used as controls for the former type of branches, by taking out the changes common to all branches of the same bank. In other words, the branch networks of the two merging banks must be overlapping, but not completely overlapping. This criterion also filters out another type of mergers where at least one of the bank in the merger is too small, and have only one branch. I end up with 335 mergers and acquisitions, 543 merged banks, 8,115 control banks, 86,887 branches and 691,390 observations in my final branch-year sample.

I report branch level and bank level summary statistics in Table 3.2.3 Panel A and B. It is worth noting that we do see a significant difference in deposit growth between branches with opponent branches nearby and those without. This is expected since the placements of branch offices are carefully made decisions by the banks, with a lot of factors considered. On the other hand, branches of the banks not involved in mergers and acquisitions seem to be more comparable with branches experienced a merger with opponent branches nearby, in terms of deposits. This highlights the necessity of controlling for the changes of these branches, while we are trying to identify the *competition effects* by comparing merging branches with or without competing branches nearby. We can also see the surviving banks are way larger than the nonsurviving banks and other banks in the same county, in terms of size. This is intuitive since it is usually the larger banks who initiate a merger or acquisition. They are more likely to be large national and/or multinational banks. However, in terms of leverage and loan-to-deposit ratio, we see little differences across the three groups.

To combine the data set above with HMDA data, I first map the geographical coordinates of the branches to census tracts from corresponding census waves. This step is done by computing the distance from each branch to the centroids of all

Panel A. Branch Characteristics

	Merge Close	Merge Far	Other
Deposits	58,449	63,249	55,705
	(218,746)	(507,929)	(522,069)
Deposit growth	10.84	5.85	9.94
	(31.14)	(24.07)	(25.91)

Panel B. Bank Characteristics

	Surviving	Nonsurviving	Other
Total Assets	15,420	1,361	551
	(61,767)	(4,842)	(4,018)
Loans/Assets	0.694	0.685	0.662
	(0.125)	(0.134)	(0.155)
Loans/Deposits	0.900	0.839	0.807
	(0.174)	(0.192)	(0.214)

Panel C. Loan Applications

	Merge Close	Merge Far	Other
Denial	0.173	0.175	0.175
	(0.378)	(0.380)	(0.380)
Loan Amount	207	198	174
	(438)	(388)	(348)
Appli. Income	114	105	98
	(198)	(165)	(154)

Table 3.1: **Summary Statistic.** Means and standard deviations are reported. Standard deviations are in the parentheses. All summary statistics are computed at one year before their corresponding transactions. Column 2 of Panel A includes all branches of merged banks with an opponent branch near by. Column 3 includes all branches of merged banks without an opponent branch near by. Column 4 includes all branches not involved in the merger in the same county as the merged branches. Deposits are in US dollars. Deposit growth is in percentage points. Column 2 of Panel B includes all banks that survived the mergers and acquisitions. Column 3 includes all banks involved in the mergers and acquisitions that ceased to exist as an independent entity after the transactions. Column 4 includes the banks that have never been in a merger or acquisition. Total assets are in millions of US dollars. Column 2 of Panel C summarizes over all loan applications in census tracts where there are branches involved in a merger that are within 10km. Column 3 includes the census tracts without such branches. Column 4 includes the census tracts with no branches participating in M&As. Loan amount and applicant income are annual income in thousands of US dollars.

census tracts. Branches are matched to the census tracts with the shortest distance. This method yields satisfactory matching results. I check the matching quality by comparing the branch county reported in the Summary of Deposits data set with the census tract county in the US census data set. The check shows less than 5% of the branches are matched with the wrong census tracts as the county information from the two data sets disagree. I drop all these branches.

Then loan applications from HMDA are matched to all the branches that are located in the same census tract as the property in that application. In other words, the final sample consists of all pairwise combinations of branches and loan applications matched according to their census tracts. This gives me a data set with repeated cross sections of loan applications. Upon inspection of the matching results, I find data availability and matching quality prior to 2005 are much poorer: Only 20% of observations in my branch-year sample can by matched with HMDA data by census tract before 2005, but more than 90% of the observations can be matched after 2005. Several loan characteristics such as rate spread is only available after 2005. So I only keep the observations post 2005. The final sample has more than 112 million observations in 30,692 census tracts, 230 counties from 2005 to 2014. Panel C of Table (3.2.3) presents the loan level summary statistics. We can see in terms of loan amount and applicant income, census tracts with mergers and acquisitions are higher than those without. Furthermore, census tracts with branches involved in mergers that have opponent branches nearby have higher average loan amount and applicant income, compared to the census tracts with isolated branches involved in mergers. These two comparisons may reflect the fact that census tracts with competing branches closer to each other correspond to more densely populated areas, and the property prices are expected to be higher.

Note that in this loan application sample, $Close$ and $Merge$ are still defined the same way as in the branch level sample. It is worth discussing the potential problems with this definition, when trying to explore the effects of the bank mergers on mortgage loan applications. Ideally, a sample of loan applications with observable originating branches is best suited for this task. When originating branches are not observable, as in HMDA data, there are two sources of potential complications introduced by matching loan applications and branches according to census tracts. First, this matching procedure will introduce misclassification error: an applicant may or may not apply for mortgage loans at branches located in the same census tract as his/her property. Previous literature, for example Petersen and Rajan (2002); Degryse and Ongena (2005); DeYoung et al. (2008) among others, has documented that physical distance does play a role in the formation of lender-borrower relationship, in the context of small business loans. However, physical distance is in no way the only factor determining borrowing outcomes. Borrowing and lending decisions are made by considering various factors including but not limited to interest rates, traveling cost, etc. In terms of the objective of this paper, the misclassification, as long as it is not biased in a systematic way, will only attenuate the effects, if there exist any effects. The second complication is that one may find variables $Close$ and $Merge$ are hard to interpret. As these variables are defined on the branch level, especially when there are multiple branches with different treatment status located in the same census tract. A more intuitive way of constructing the sample is to come up with corresponding measures of $Close$ and $Merge$ at census tract level, so applications in census tracts affected by mergers can be compared to applications in census tracts not affected by mergers. In fact, using $Close$ and $Merge$ defined at branch level, and forming pairwise combinations of branches and loan applications according to census tracts is equivalent to defining new measures of $Close$ and $Merge$ at census tract level. To better understand this, one can think of $Close$ and $Merge$ here as the treatment intensity measures at the census tract level: in a census tract with majority of branches involved in mergers, the average $Merge$ will be closer to 1 relative to the census tracts with only small fraction of branches involved in mergers. This is similar for *Close*. So I can still identify the *efficiency* and *competition effects* at census tracts level using the treatment variables defined at the branch level. In this way, corresponding coefficients are identified from the variation in the proportion of branches with opponent branches nearby, and branches participating in M&As across census tracts.

3.3 Results

3.3.1 Deposit Growth

In Table 3.3.1, I report the first main results of this paper. I implement the regression in (3.1), along with other similar specifications, to identify the *efficiency* and *competition effects* of bank M&As on branch level deposit growth.

Column 1 presents the results of the simplest regression. The reported estimate suggests merging branches with an opponent branch within 10km experience a 1.4 percentage points drop in deposit growth compared to all other branches. This is both statistically and economically significant, considering these branches have around 10% growth in deposits prior to the transactions. However, this estimate cannot be interpreted as the *competition effects* of bank consolidations. It could be contaminated by a number of factors, including *efficiency effects*, mean reversion of some banks involved in the transactions, etc..

Column 2 includes one more additional term $Merge \times Post$, which controls for common change among all merging branches relative to banks not involved in M&As. Two concerns prevent us from being able to interpret the coefficient of $Close \times Post$ as *competition effects* and the coefficient of $Merge \times Post$ as *efficiency effects*. First concern is that merging branch may have larger changes in deposit growth always than other branches. For example, if banks located in areas where there is high economic

Variables	(1) Δdep	(2) Δdep	(3) Δdep	(4) Δdep
$Close \times Post$	-1.424**	-1.999***	-3.223***	-3.450***
	(0.645)	(0.635)	(0.716)	(0.686)
$Merge \times Post$		0.5514**	1.903***	2.350***
		(0.229)	(0.249)	(0.300)
Branch FE	No	No	Yes	Yes
County×Year FE	No	No	No	Yes
Observations	691,390	691,390	691,390	682,797
Adj. R^2	0.001	0.004	0.176	0.279

Table 3.2: **Changes in deposit growth.** This table presents the results of regression $\Delta dep_{ict} = \alpha_0 + \alpha_1 Close_i \times Post_t + \alpha_2 Merge_i \times Post_t + \mu_i + \nu_c \times t + \epsilon_{ict}$, i is the index for branches, c is the index for counties, and t is the index for years. Branch fixed effects are captured by μ_i, County×Year fixed effects are captured by $\nu_c \times t$. Observations are at branch-year level. Δdep is deposit growth in percentage points. $Close$ is a dummy variable equal to 1 if there exists merger counterpart branches within 10km. $Merge$ is a dummy variable equal to 1 if the branch is involved in a merger or acquisition. $Post$ is a dummy variable 1 for years after merger years. Standard errors are in parentheses. The sample includes mergers and transactions from 1997 to 2014, and includes 3 years before and after each transaction whenever available. All standard errors are clustered at county level. *, **, *** denotes significance at 10%, 5%, 1% respectively.

growth are more likely to participate in mergers and acquisitions, we may be able to observe the same pattern in the coefficient of $Merge \times Post$. The effects identified does not reflect the consequence of the mergers at all. Similarly, there could well be branch level unobservable characteristics that are determining the location and changes in deposit growth. The coefficient of $Close \times Post$ could be spuriously capturing this unobservable characteristics instead of *competition effects* as it is intended to do. The potential problem can be addressed by including branch fixed effects, which controls for all branch level time-invariant characteristics. The results are reported in Column 3.

Finally, Column 4 includes county-year fixed effects which takes out county level time varying conditions. One could argue that banks predict many counties they have presence in will experience a certain economic change in the near future, thus deciding to merge to either avoid the negative impact of such change or maximize the positive impact of such change, given that these M&As provide the means to take advantage of such local economic changes. This effect will appear in both coefficients reported. What is important here is that this local economic change should generate similar impact on all branches in the county. Therefore, county-year fixed effects are able to address this concern, by taking out common movement in the variable of interest within a county in each year.

To sum up, Table 3.3.1 provides evidence that within the sample, merged branches on average have gained 2.3 percentage points in deposit growth compared to branches not involved in mergers or acquisitions, which can be interpreted as the *efficiency effects*. Moreover, *competition effects* lead to a drop in deposit growth by 3.5 percentage points for branches that experienced a decrease in local competition, relative to those that did not.

The economic mechanism behind the results on deposit growth is not immediately clear. One can imagine that markets where merging branches locate near each other are usually in densely populated areas. These branches should benefit more from a local economy of scale. For example, local advertisement is very effective in these areas because the cost is shared among many branches in the local market. This idea seems to suggest the branches located in these areas are more effective in attracting deposits. All else equal, we should expect to see the deposit growth to be even higher for these branches, which is opposite to what we see in Table 3.3.1.

We can also imagine the following mechanism where branches that experienced larger drop in local competition do decrease their demand for deposits. Gaining market power in local markets allows the branches to restrict their lending activity, and charge higher interest rates on the loans they issue, just as in a Cournot competition environment. In this case, lowering deposits in these branches can save them cost on interest payments to depositors. To better under stand the results, and to explore the impact on access to credit, I implement regression (3.2) on the loan application level data, whose results are presented in Table (3.3.2).

3.3.2 Mortgage Loan Applications

Table 3.3.2 presents the changes in mortgage loan application activities. Column 1 and 2 look at the changes on the probability of getting denied. The dependent variable *Denial* is a dummy variable equal to 100 if the loan got denied, and 0 otherwise. So all the coefficients can be interpreted as in percentage points. Column 1 of Table (3.3.2) reports the results without any loan level controls. First we see a significant increase in denial probability overall for regions with more branches involved in M&As. There is also weak evidence that the overall denial probability increases even more in the census tracts where merging branches locate near each other. Column 2 includes all loan level controls, including applicant income, loan amount, loan type and loan purpose. It is very intuitive to see applicant income is very strongly negatively correlated with denial probability, and loan amount is strongly negatively correlated with denial probability. The magnitudes of the coefficients, however, are relatively small. One possible explanation is that these loans are all secured by the property. The coefficient of $Merge \times Post$ is positive and significant, which may suggest that due to the consolidation, the merged banks become more effective at selecting out high credit quality borrowers. It could also suggest that as larger banks, they attract more loan applications, especially from low credit quality borrowers. With the approval standard stays the same, we may see an increase in denial rate. More interestingly, the coefficient before $Close \times Post$ is also positive and significant. It says the denial probability in census tracts with more merging branches close to each other saw an increase in denial probability by 0.32 percentage points, relative to the census tracts without merger branches close to each other. Given the sample average denial probability of about 17.5%, a 0.32 percentage points increase is economically meaningful. Combining with the results on deposit growth, the findings suggest that the local branches are actively utilizing their market power to limit supply of credit to potential mortgage loan borrowers, thus they also do not need as much deposits. Column 3 reports results of similar regression, but allowing for the dependencies of denial probability on loan amount and applicant income to differ across counties. Doing this does not change the two main coefficients of interest much, if at all.

To examine if the changes in denial rates are driven by changes in loan applications, I collapse the loan application level data into census tracts level. Specifically, I use the count of mortgage loan applications for each census tract year as the dependent variable. The results are reported in Column 4 and 5 of Table 3.3.2. We can clearly see the census tracts where merging branches have opponent branches nearby actually have larger declines in loan application counts. Hence, it is unlikely the increase in denial rates documented is due to an influx of low credit quality applicants. This provides more evidence that the branches in areas which experienced a large decline

Variables	(1) *Denial*	(2) *Denial*	(3) *Denial*	(4) # Loan App	(5) # Loan App
$Close \times Post$	0.288***	0.278**	0.275**	-9.985*	-10.153**
	(0.110)	(0.114)	(0.114)	(5.121)	(5.083)
$Merge \times Post$	0.130***	0.085**	0.085**	-6.136***	-6.027***
	(0.040)	(0.040)	(0.040)	(2.254)	(2.262)
Loan Amount		0.004***			0.008***
		(0.000)			(0.003)
Appli. Income		-0.007***			0.368***
		(0.000)			(0.078)
Other Controls	No	Yes	Yes	No	No
Heterogeneous Slope	No	No	Yes	N/A	N/A
Census Tract FE	Yes	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes	Yes
Observations	112,130,285	98,698,870	98,698,870	244,628	244,517
Adj. R^2	0.026	0.052	0.052	0.841	0.842

Table 3.3: **Changes in mortgage loan applications.** Column 1 to 3 reports the results of regression $y_{ijct} = \alpha_0 + \alpha_1 Close_i \times Post_t + \alpha_2 Merge_i \times Post_t + X_i + \mu_j + \nu_c \times t + \epsilon_{ijct}$, where i is the index for loan applications, j is the index for census tracts, c is the index for counties, and t is the index for years. X_i represents loan application specific controls. μ_j captures census tract fixed effects. Heterogeneous slope allows for heterogeneous coefficients for applicant income and loan amount across different counties. Panel A column 4 to 5 report the regression results of $\#Loan\_App_{jct} = \alpha_0 + \alpha_1 Close_j \times Post_t + \alpha_2 Merge_j \times Post_t + \mu_j + \nu_j \times t + \epsilon_{jct}$. Panel B reports the results of regression $Income_{ijct} = \alpha_0 + \alpha_1 Close_i \times Post_t + \alpha_2 Merge_i \times Post_t + \mu_j + \nu_c \times t + \epsilon_{ijct}$ for different subsamples sorted by if the loan application was accepted. *Denial* is a dummy variable equal to 100 if the loan application was denied, and 0 otherwise. # Loan App is the number of mortgage loan applications in each census tract-year. *Close* is a dummy variable equal to 1 if there exists merger counterpart branches within 10km in the census tract. *Merge* is a dummy variable equal to 1 there exists branches of merging banks in the census tract. Loan amount and applicant income are in thousands of US dollars. Other controls include loan type and loan purpose. The sample period is from 2005 to 2014. Column 3 and 4 are implemented on census tract-year sample. Standard errors are in parentheses. All standard errors are clustered at census tract level. *, **, *** denotes significance at 10%, 5%, 1% respectively.

of competition due to bank consolidations are tightening the supply of mortgage loans after the consolidations, even after controlling for applicant income, a proxy for borrower creditworthiness.

Column 5 and 6 presents the results when I use rate spread as the dependent variable. Column 5 seems to suggest there is an *efficiency effect* of bank consolidations, since the census tracts with mergers happen have a drop in rate spread. At its face value, the finding is consistent with Kahn et al. (2005), who find that bank consolidations lead to lower rates on automobile loans which are secured. But here the effects are gone after controlling for the applicants characteristics. Notice that we cannot draw the conclusion that mergers do not have impact on mortgage loan prices just based on these results. One of the most important concern here is the data quality. Rate spread here is by no means a perfect measure of loan prices. The reasons are two folds: firstly banks do not report the spread for any non first-lien or subordinate-lien loans, secondly, even if the loan has one of the two lien status, banks do not have to report the spread below thresholds. Hence, the rate spread here is not representative of the overall mortgage loan prices, and it is left censored. The sharp decline of observation count in Column 5 and 6, compared to Column 1 and 2, is because rate spreads on most loan applications are not reported.

3.3.3 Subsample Analysis

The sample used for Table 3.3.1 includes mergers and acquisitions regardless of whether or not the transaction had received government assistance. Since government-assisted transactions usually involve failed banks, the recovery of these banks after the transactions may pose challenges to identification, as discussed in Section 3.2.2. At the same time, there has been discussion about how to improve the efficiency of government-assisted M&As attempting to saving failed banks. It is itself important to be able to assess the consequences of these transactions. To verify if the results

Variables	(1) Δdep	(2) Δdep	(3) Δdep	(4) Δdep
Subsample	No Assist	Assist	Normal	Recessions
$Close \times Post$	-1.964***	-7.612***	-2.794***	-5.052**
	(0.790)	(2.137)	(0.722)	(2.445)
$Merge \times Post$	1.416***	5.110***	2.255***	1.689
	(0.305)	(0.621)	(0.289)	(1.099)
Branch FE	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes
Observations	540,999	134,358	550,323	117,285
Adj. R^2	0.189	0.199	0.1746	0.2234

Table 3.4: **Subsample results for deposit growth.** This table implements the regression $\Delta dep_{ict} = \alpha_0 + \alpha_1 Close_i \times Post_t + \alpha_2 Merge_i \times Post_t + \mu_i + \nu_c \times t + \epsilon_{ict}$ on different subsamples. The first two columns are sorted by whether there is any government assistance involved in the merger. The last two columns are sorted by whether the merger occurred in an NBER recession. Δdep is deposit growth in percentage points. $Close$ is a dummy variable equal to 1 if there exists merger counterpart branches within 10km. $Merge$ is a dummy variable equal to 1 if the branch is involved in a merger or acquisition. $Post$ is a dummy variable 1 for years after merger years. Standard errors are in parentheses. The sample includes mergers and transactions from 1997 to 2014, and includes 3 years before and after each transaction whenever available. "Assist" means the transactions have received assistance from government agencies. "Recession" means the transactions occur during NBER recessions. All standard errors are clustered at county level. *, **, *** denotes significance at 10%, 5%, 1% respectively.

presented in Table 3.3.1 and 3.3.2 are indeed universal phenomena, and to explore the differential effects with or without government assistance, it is meaningful to repeat the exercise for government-assisted and non-government-assisted transactions.

Column 1 and 2 of Table 3.3.3 report the results of the full regression specification under the two subsamples. We see qualitatively the same results as in the full sample. Another immediate observation is that the subsample with government assistance shows much higher *efficiency effects*. One potential concern is that the coefficient $Post \times Merge$ does not only captures the *efficiency effects*, but also the recovery of the failed banks. This is indeed the case since the coefficient is averaged across acquirer and target branches. If the target was in really bad shape before the merger, and the merger event just diverged some customers of the acquirer to the newly acquired branches which were previously owned by the failed bank, we will see a very large increase in deposit growth for these branches. It is overreaching to interpret these changes as *efficiency effects*. I will discuss more about this concern in Section 3.3.6, where I show evidence that the branches of the target banks, which are most likely the failed bank in government-assisted cases, are not driving the results we see here.

Column 3 and 4 explores the subsamples of whether or not the transaction occurs during an NBER recession. There are two NBER recessions during my sample period: 2001Q1 to 2001Q4, and 2007Q4 to 2009Q2. I identify 46 transactions occur during recessions, and 289 occur during expansion. We see quantitatively similar results for mergers and acquisitions that happen during normal times. An interesting finding is that the transactions that happen in recessions show very small and insignificant *efficiency effects*, but much stronger *competition effects*. This could suggest that it is difficult for consolidated banks to attract deposits, even with improved efficiency. Alternatively, this could also suggest the banks which endogenously choose to merge during recession have very little synergy benefit from the mergers. The stronger *competition effects* suggest that the banks may be compensating the low overall gains from consolidation, by more actively exercising their market power.

So far I have presented some interesting differences in terms of effects of bank M&As on deposit growth across transactions with or without government assistance, and transactions during or out of recessions. I repeat the analysis with the mortgage loan application sample. Table 3.3.3 presents the results. I use the same specification as Column 2 of Table 3.3.2 here. Column 1 and 2 show the comparison between government-assisted and non-government-assisted cases. The denial rates in regions more affected by the M&As tend to go up on average. More interestingly, for cases without government assistance, there is little variation in the increase in denial rates

	(1)	(2)	(3)	(4)
Variables	*Denial*	*Denial*	*Denial*	*Denial*
Subsample	No Assist	Assist	Normal	Recessions
$Close \times Post$	-0.119	1.148***	-0.356***	-0.457
	(0.147)	(0.224)	(0.121)	(0.400)
$Merge \times Post$	0.093*	0.210***	-0.043	0.385***
	(0.053)	(0.067)	(0.042)	(0.120)
Other Controls	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes
Observations	58,910,275	39,788,575	76,868,180	21,830,680
Adj. R^2	0.050	0.054	0.050	0.057

Table 3.5: **Subsample results for loan applications.** This table implements the regression $y_{ijct} = \alpha_0 + \alpha_1 Close_i \times Post_t + \alpha_2 Merge_i \times Post_t + X_i + \mu_j + \nu_c \times t + \epsilon_{ijct}$ on different subsamples of loan application level data. The first two columns are sorted by whether there is any government assistance involved in the merger. The last two columns are sorted by whether the merger occurred in an NBER recession. *Denial* is a dummy variable defined on loan application level equal to 100 if the loan application was denied, and 0 otherwise. *Close* is a dummy variable defined on branch level equal to 1 if there exists merger counterpart branches within 10km. *Merge* is a dummy variable defined on branch level equal to 1 if the branch is involved in a merger or acquisition. *Post* is a dummy variable 1 for years after merger years. Standard errors are in parentheses. Other controls include loan amount, applicant income, loan type and loan purpose. The sample includes mergers and transactions from 2005 to 2014, and includes 3 years before and after each transaction whenever available. "Assist" means the transactions have received assistance from government agencies. "Recession" means the transactions occur during NBER recessions. All standard errors are clustered at census tract level. *, **, *** denotes significance at 10%, 5%, 1% respectively.

across regions with merging opponent branches closer or farther from each other. That is, there seems to be very small, if at all, *competition effects* for non-government-assisted M&As. On the other hand, for the cases with government assistance, we see the denial rate in regions where branches of the two merging institutions locate closely increase by as much as 4 times as the average increase in denial rates in other regions influenced by the same transactions. These results, together with the results in point out a trade-off of these government-assisted M&As: they do demonstrate higher *efficiency gains*, but at the same time, the banks involved seem to exercise more market power they gain from these transactions. Column 3 and 4 of Table 3.3.3 show the comparison for transaction that happen during recessions and normal times. Interestingly, in normal times, the increase in denial rates is only concentrated in regions where branches of merging banks locate closely. Whereas in recessions, we do not observe such variation across regions differing in proportion of merging branches locating closely. Instead, we see pretty consistent increase in denial rates across all regions affected by the mergers.

3.3.4 High-income v.s. Low-income Applicants

So far the results seem to be more consistent with the predictions first made by Klein (1971), which says lower competition will lead to lower credit supply and higher rates. This is exactly what column 1 through 3 of Table 3.3.2 show, since we do see increase in denial rate even after controlling for applicant income and loan amount, together with some additional loan characteristics. Petersen and Rajan (1995) predicts lower competition leads to higher supply of credit due to information asymmetry. In reality, these two economic mechanisms are most likely present at the same time. Petersen and Rajan (1995) also provides another implication that is potentially testable with the data available here. The basic intuition behind this theory is that competition limits banks ability to charge high rates on high credit quality borrowers, thus limiting the subsidy they are able to provide to lower credit quality borrowers. In equilibrium, we will see lower credit supply, especially among low credit quality borrowers, when there is higher competition. This mechanism suggests that the borrower composition must change before and after the changes in competition. Mapping to the data available in this paper, a testable implication is that more low-income borrowers will be priced out of the mortgage loan market, due to decline in subsidy available from the lenders, so we expect to see denial rates increase more among low income applicants.

To test this implication, I first compute the median applicant income for each census tract-year. Then applicants are divided into high-income and low-income group depending on if he/she is above or below the median income for that census tract-year. Then the high-income and low-income dummy variables are interacted with the $Close \times Post$ and $Merge \times Post$ to explore the differential changes in denial rates for high- and low-income applicants. The results are reported in Table 3.3.4. Now the *competition effects* and *efficiency effects*, previously captured by $Close \times Post$ and $Merge \times Post$, are now separately identified for high-income and low-income applicants.

Column 1 of Table 3.3.4 reports the results for the full sample. One immediate observation is that the *competition effects* are mostly driven by low-income applicants. That is, in the markets where there is a larger decline in inter-bank competition due to the mergers, low-income applicants see a much larger increase in denial rates compared to the high-income applicants in the same markets. This evidence is in fact inconsistent with the mechanism described in Petersen and Rajan (1995), which predicts low quality borrowers should have better access to credit, since their lenders can subsidize more by charging more from the good quality borrowers due to their gain in market power. The results in this paper suggest that the decline in local inter-bank competition on average harms low-income borrowers. I then extend the analysis to cases with or without government assistance and cases during recessions or

Variables	(1) *Denial*	(2) *Denial*	(3) *Denial*	(4) *Denial*	(5) *Denial*
Subsample	Full	No Assist	Assist	Normal	Recession
$Close \times Post \times High\_inc$	0.127	-0.198	0.700***	0.172	-0.258
	(0.151)	(0.194)	(0.271)	(0.160)	(0.504)
$Close \times Post \times Low\_inc$	0.426***	-0.042	1.583***	0.549***	1.134**
	(0.140)	(0.180)	(0.244)	(0.148)	(0.556)
$Merge \times Post \times High\_inc$	2.741***	2.984***	2.890***	2.689***	2.816***
	(0.053)	(0.053)	(0.080)	(0.058)	(0.132)
$Merge \times Post \times Low\_inc$	-2.655***	-2.893***	-2.554***	-2.864***	-2.106***
	(0.058)	(0.070)	(0.082)	(0.062)	(0.134)
Other Controls	Yes	Yes	Yes	Yes	Yes
Census tracts FE	Yes	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes	Yes
Observations	98,698,870	58,910,275	39,788,575	76,868,180	21,830,680
Adj. R^2	0.054	0.053	0.056	0.053	0.059

Table 3.6: **Differential effects for high-income and low-income applicants.** Column 1 to 3 reports the results of regression $Denial_{ijct} = \alpha_0 + \alpha_1 Close_i \times Post_t \times High\_inc_i + \alpha_2 Close_i \times Post_t \times Low\_inc_i + \alpha_3 Merge_i \times Post_t \times High\_inc_i + \alpha_3 Merge_i \times Post_t \times Low\_inc_i + OtherInteractions + X_i + \mu_j + \nu_c \times t + \epsilon_{ijct}$, where i is the index for loan applications, j is the index for census tracts, c is the index for counties, and t is the index for years. X_i represents loan application specific controls including loan type and loan purpose. μ_j captures census tract fixed effects. $High\_inc$ and Low_inc are dummy variables equal to one when the applicant's income is above or lower than the median income respectively for that census tract-year. Column 1 implements the regression on the full loan application sample. Column 2 to 3 implement the regression on mergers cases with and without government assistance. Column 4 to 5 implement the regression on cases happen out of or during NBER recessions. Standard errors are reported in parentheses, all clustered at census tract level. *, **, *** denotes significance at 10%, 5%, 1% respectively.

not. As shown in column (3) and (5) of Table 3.3.4, cases with government assistance and during recession appear to cause much larger harm to low-income borrowers' access to mortgage loans, as the coefficients on $Close \times Post \times Low\_inc$ are 2 to 3 times that of the full sample average.

Another interesting observation is that on average in areas affected merged branches, regardless of whether there used to be a competing branch of the merger counterpart nearby, we see an increase in denial rates for high-income applicants, and a decrease in denial rates for low-income applicants. This could be due to an improvement of overall applicant credit quality following the mergers, which leads to a lower denial rate for low-income borrowers. And at the same time, the merged banks can better screen applicants' credit quality, so some high-income borrowers may prove to be not so creditworthy, hence we see the increase in denial rates for high-income borrowers. However, further investigation does not seem to support this story: untabulated results show there is little change in applicant income before and after the mergers.

3.3.5 Dynamic Effects

Erel (2011) documents some reversal in spreads of small business loans following bank mergers. Specifically, larger acquirers like to reduce spreads in newly entered markets to gain market shares, then later increase the spreads. It would be interesting to look at if there is reversal in the changes documented so far in this paper. I created 3 new year dummy variables $Post\tau$, $\tau = 1, 2, 3$, which equal to 1 τ years after the mergers. I then run the same regressions using deposit growth and loan application data. The results are reported in Table 3.3.5. I do not find any reversal in the changes in deposit growth and denial rates. An interesting comparison is that the *efficiency effects* on deposit growth start to appear as early as the first year following the mergers, while the effects on denial rates do not show up until the third year after the mergers. This could be due to longer time needed to integrate credit screening system when assessing loan applications following the mergers. The negative coefficients on $Close \times Post\tau$ in column 1 suggest that branches with merger counterpart branches nearby see lower deposit growth in all 3 years following the mergers. And positive coefficients on the same terms in column 2 suggest that in areas with merging branches close to each other experience increase in denial rates in all three years following the mergers. The results suggest that both *competition* and *efficiency effects* identified in this paper do not change direction for at least three years following mergers.

3.3.6 Acquirer v.s. Target

As mentioned in Section 3.2.2, including $Merge \times Post$ extract all changes that are the same for all merged branches, thus allowing me to identify *competition effects* with $Close \times Post$, which relies on the cross section variation of whether or not there is a merger counterpart branch nearby. However, interpreting $Merge \times Post$ directly as *efficiency effects* may be overreaching, especially I include the mergers case with failed banks in the sample. Taking deposit growth as an example, the concern is that failed banks may have very little deposits left in the branches, they may have been suffered from runs. These branches are likely to see very high deposit growth following the mergers after they are rebranded under the larger, and financially healthier acquirer. This recovery effects may drag up the average change in deposit growth for the consolidated institution, but conceptually has nothing to do with efficiency gain. To address this concern, I explore the cross-section differential in the effects identified before in this paper among acquiring and target institutions. If the above mechanism is indeed what drives the results, we should see the *efficiency effects* mostly coming from target institutions. I define acquirer as the surviving institution of a merger reported in the bank merger data set from Chicago Fed, and target as the nonsurviving institution.

Variables	(1) Δdep	(2) $Denial$
$Close \times Post1$	-2.864***	0.337***
	(0.878)	(0.123)
$Close \times Post2$	-1.636*	0.163
	(1.055)	(0.142)
$Close \times Post3$	-5.958***	0.323**
	(0.952)	(0.160)
$Merge \times Post1$	1.194***	0.078
	(0.403)	(0.049)
$Merge \times Post2$	3.026***	0.018
	(0.375)	(0.052)
$Merge \times Post3$	2.841***	0.163***
	(0.396)	(0.056)
Other Controls	N/A	Yes
Branch FE	Yes	No
Census tract FE	No	Yes
County×Year FE	Yes	Yes
Observations	682,797	98,698,870
Adj. R^2	0.181	0.052

Table 3.7: **Dynamic effects of bank mergers.** Column 1 implements the regression $\Delta dep_{ict} = \alpha_0 + \sum_{\tau=1}^{3} \alpha_{1,\tau} Close_i \times Post\tau_t + \sum_{\tau=1}^{3} \alpha_{2,\tau} Merge \times Post\tau_t + \mu_i + \nu_c \times t + \epsilon_{ict}$. Δdep is deposit growth in percentage points. $Close$ is a dummy variable defined on branch level equal to 1 if there exists merger counterpart branches within 10km. $Merge$ is a dummy variable defined on branch level equal to 1 if the branch is involved in a merger or acquisition. $Post\tau$ is a dummy variable equal to1 for τ years after merger, and 0 otherwise. Standard errors are in parentheses. Other controls include loan amount, applicant income, loan type and loan purpose. The sample includes mergers and transactions from 2005 to 2014, and includes 3 years before and after each transaction whenever available. "Assist" means the transactions have received assistance from government agencies. "Recession" means the transactions occur during NBER recessions. All standard errors are clustered at census tract level. *, **, *** denotes significance at 10%, 5%, 1% respectively.

Variables	(1) Δdep	(2) $Denial$
$Close\_Acquirer \times Post$	-2.042**	0.306**
	(0.916)	(0.129)
$Close\_Target \times Post$	0.243	0.477**
	(1.861)	(0.219)
$Acquirer \times Post$	3.116***	-0.018
	(0.312)	(0.042)
$Target \times Post$	-0.585	0.126
	(0.844)	(0.114)
Other Controls	N/A	Yes
Branch FE	Yes	No
Census Tract FE	No	Yes
County×Year FE	Yes	Yes
Observations	682,797	98,698,870
Adj. R^2	0.181	0.052

Table 3.8: **Differential effects for acquirers and targets.** Column 1 implements the regression $\Delta dep_{ict} = \alpha_0 + \alpha_1 Close\_Acquirer_i \times Post_t + \alpha_2 Close\_Target_i \times Post_t + \alpha_3 Acquirer_i \times Post_t + \alpha_4 Target_i \times Post_t + \mu_i + \nu_c \times t + \epsilon_{ict}$. Δdep is deposit growth in percentage points. $Close\_Acquirer$ is a dummy variable defined on branch level equal to 1 if there exists merger counterpart branches within 10km and if that branch is owned by the acquiring institution before the merger. $Close\_Target$ is a dummy variable defined on branch level equal to 1 if there exists merger counterpart branches within 10km and if that branch is owned by the target institution before the merger. $Acquirer$ is a dummy variable defined on branch level equal to 1 if the branch is owned by the acquiring institution involved in the merger. $Target$ is a dummy variable defined on branch level equal to 1 if the branch is owned by the target institution involved in the merger. $Post$ is a dummy variable equal to1 for years after the merger. Standard errors are in parentheses. Other controls include loan amount, applicant income, loan type and loan purpose. The sample includes mergers and transactions from 2005 to 2014, and includes 3 years before and after each transaction whenever available. Standard errors are clustered at county level for the branch level regression and at census tract level for loan application level regression. *, **, *** denotes significance at 10%, 5%, 1% respectively.

The regression results are reported in Table 3.3.6. Column 1 shows the results using branch level sample. We can see the *efficiency effects* are in fact driven by acquirer branches, in contrary to the prediction mentioned above, which alleviates the concern that recovery effects may be driving the results. At the same time, we can see for branches with merger counterpart branches nearby, the decline in deposit growth mostly comes from acquirer branches. Column 2 shows the results using loan application data. We can see the *efficiency effects* on denial rates are not driven by any of acquirers or targets. But collectively, there is an increase in denial rates on average for the areas affected by the mergers, as reported in Table 3.3.2. The *competition effects* on denial rates are also similar across areas where acquirers and targets are located.

3.4 Conclusion

This paper investigates the consequences of bank consolidations on banks and consumers through *efficiency* and *competition* effects. Merged banks have an *efficiency* gain in attracting deposits on average across branches. But branches which gain more market power tend to lower deposit growth, which saves cost of interests on deposits when they can better limit the supply of mortgage loans with higher market power. There are larger increase of denial rates of mortgage loan applications in regions with larger decline in bank competition, and the results are not driven by an influx of low credit quality applicants.

In comparison of the two theories studying the implications of bank competition on credit supply and borrowing rates, Klein (1971) and Petersen and Rajan (1995), this paper presents more consistent evidence with the former one. Firstly, Klein (1971) predicts lower competition leads to lower supply of credit, which is consistent with the denial rate and deposit growth results found in this paper. Secondly, Petersen and

Rajan (1995) predicts different composition of borrowers who can get access to credit under different levels of competition. However, this paper does not find supporting evidence for this prediction.

The effects of bank consolidations on loan rates, specifically mortgage loan rates, cannot be cleanly identified due to poor data quality. It is intriguing to examine the loan pricing impact of bank consolidations with appropriate data, where the experiment design in this paper can be a very powerful tool. In fact, very limited data are available at branch level. Investigating many aspects of consequences of bank consolidations on branch level will help us better understand the economic mechanisms behind bank operations.

This paper demonstrates that bank consolidations can benefit depositors and/or borrowers in certain regions while harm those in other regions, depending on the competition changes in those regions. This points out a topic that is previously under-investigated: how do positive and negative impacts of bank consolidations distribute geographically, and what are the determinants of such distribution? Specifically, further researches can investigate the impacts on the final outcomes of the M&As of merging banks' characteristics. For example, the harm to loan-income borrowers could be especially large for mergers between banks with certain financial characteristics, as well as branch network characteristics. If policy makers have a better assessment of such potential transactions, they can better decide whether and how to step in to avoid the unwanted consequences.

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