Do low search costs facilitate like-buys-like mergers? Evidence from common bank networks*

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Abstract

We examine how search frictions affect merger outcomes. Exploiting firm connections in common bank networks (CBNs) as a channel for reducing search costs, we show that like-buys-like mergers are more probable between firms connected through a CBN. This effect is amplified if the connection has been recently formed or the network contains many plausible choices for merger partners. CBN-facilitated mergers exhibit higher synergy and lower post-merger cost of debt. We confirm that CBNs reduce search costs even after alternative explanations are considered. These findings highlight the importance of search in the process of redrawing firm boundaries.

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1. Introduction

Does search matter in the process of redrawing firm boundaries? Rhodes-Kropf and Robinson (2008) extended the literature formalized by Grossman and Hart (1986) and Hart and Moore (1990) concerning the boundaries of the firm into the assortative matching theory of complementary mergers (i.e., like-buys-like mergers). Since then, numerous studies have focused on the empirical evidence of the association between the asset complementarities of merging firms and synergistic merger outcomes (Hoberg and Phillips, 2010; Bena and Li, 2014; Lee, Mauer, and Xu, 2018). Surprisingly, the importance of search as a determinant of cross-sectional variation in asset complementarity and synergistic outcomes in mergers has garnered little attention in the literature.

In this study, we highlight the importance of search by investigating the impact of search efficiency on the merger process and outcomes. Specifically, using a firm's network affiliation as a channel for low-cost search, we study the effect of search frictions on the quality of assortative matching and investor value creation in mergers. To the best of our knowledge, this paper is the first cross-sectional study to theoretically and empirically show that a reduction in search frictions increases the likelihood of complementary mergers and post-merger synergistic value.

For the particular firm network under study, we focus on a commercial lending network consisting of a bank and its borrower firms as the channel for low-cost search for merger partners. The lending network is an ideal laboratory for studying the effect of search frictions in the corporate merger market for two reasons. First, commercial banks as financial intermediaries maintain close business relationships with a large number of borrower firms, which provide the banks with access to their key personnel and non-public information. Second, commercial banks have potential economic incentives to give counsel to borrowers and help them preserve the ability to meet debt service requirements for the loans (Leland and Pyle, 1977; Diamond, 1984; Boot, 2000). For these reasons, we predict that commercial banks have strong economic interests in reducing search frictions for borrowers seeking complementary merger partners by providing them with advice and easy access to other network constituents.

With the lending network as a low-cost channel for the search process, we extend Rhodes-Kropf and Robinson's (2008) theory of complementary mergers by developing a simple search-and-bargain model featuring rational expectations and random networks (Erdos and Renyi, 1959; Bollobas and Bela, 2001; Jackson, 2008; Banerjee, Chandrasekhar, Duflo, and Jackson, 2019).

Our model posits that firms in the merger market have economic incentives to search for merger partners with complementary assets and capture post-merger synergistic value (Rhodes-Kropf and Robinson, 2008). Each firm initiating the search faces frictions, which determine the probability of meeting the next merger candidate within a given time period. Once the firm meets a candidate, it observes a potential synergy from asset complementarity and bargains on its share of the synergy. Each firm's search efficiency affects the abundance of its outside options, which, in turn, strengthens the firm's relative bargaining power. The firm trades off between the immediate gain from merging with the current candidate and the expected gain from waiting for a better matching partner in the future. Assessing the extent of search costs, the firm endogenously sets a threshold for the minimum level of complementarity between its assets and the potential merger partner's assets. If the firm and the current candidate have a degree of complementarity that is greater than the threshold, the firm merges with the candidate; if not, the firm moves on and waits for the arrival of the next candidate.

A bank that has lending relationships with the firms can potentially assist in the bidders' search efforts by providing them with advice and access to the key personnel or private information of other firms in its lending network.[4] The bank, with the goal of maximizing the value of its existing loan portfolio, faces a short call option-like payoff schedule (Jensen and Meckling, 1976). Hence, the bank will assist a bidder only if its assistance can increase the synergistic value of a merger without the risk of asset substitution,

[4] Masulis and Simsir (2018) show that the majority (65%) of merger deals are initiated by acquirers. On the basis of their findings, we focus on acquirer-initiated search. However, similar inferences can be drawn even if we construct the model focusing on target-initiated search when the targets are financially distressed and desperate for liquidity. Section 2.4 discusses the main features of the target-initiated search model. Masulis and Simsir (2018) show that the target-initiated deals mostly involve targets in severe liquidity shortage. From these findings, we argue that whether a deal is initiated by an acquirer or a target has little empirical relevance for our study.

which potentially reduces the value of outstanding loans extended to the firms before the merger (Jensen and Meckling, 1976).

If the bank proceeds to provide assistance in the search of a bidder who has outstanding loans from the bank, the bidder can enjoy a decreased search cost, which enables the bidder to meet more candidates within a given period. The more frequent meetings with candidates in turn increase the bidder's probability of meeting highly complementary target candidates and of achieving greater post-merger synergy. Furthermore, the bidder exploits an increase in its outside options owing to the bank's assistance as bargaining leverage in the negotiation with the candidate and attains a greater share of the synergy. The candidate's shareholders are willing to remain in the negotiation and eventually sell the firm under the terms set forth by the bidder as long as the dollar value of the candidate's gain from the deal is greater than its potential gain from the best of the available alternatives. Rationally anticipating the positive effect of the bank's assistance, the bidder endogenously raises the minimum threshold for the degree of complementarity between its assets and the merger partner's assets.

In summary, our model's equilibrium conditions have several testable implications. First, if combining complementary assets under one firm is an important motivation for mergers, as shown by Rhodes-Kropf and Robinson (2008), a reduction in search frictions through a shared lending network increases the likelihood of mergers of greater complementarity and higher synergistic value between the network constituents. Second, the bank's assistance in the search process affects the bidder's bargaining power more positively than the target's. Third, the bank's participation conditions indicate that the bank will assist a bidder only when doing so increases the value of outstanding loans and thereby benefits the bank.

Using firm connections through a common bank network (CBN) as a proxy for low search costs, we derive the following five empirical predictions from the equilibrium conditions.

H1: Firms connected through a CBN are more likely to engage in a complementary merger than firms not connected through such a network.

H2: The search friction-reducing effect of a CBN is more pronounced when the connection is made of recently originated loans than when it is made of old or expired loans.

H3: Mergers between firms connected through a CBN create greater synergistic value.

H4: Acquirers retain a greater share of merger synergy than targets in CBN mergers.

H5: Greater synergistic value of CBN mergers is achieved without substantially increasing the asset volatility of the combined firms.

These predictions broadly test the model's main implication that low search costs facilitate complementary and synergistic mergers. To test these predictions, we first collect information on 1,683 completed all-US industrial public firm mergers announced during the sample period of 1992 to 2016 from the Securities Data Company (SDC) database. Then, we identify lending relationships between our sample firms and lending institutions for the period preceding the merger announcement using Thomson Reuters LPC's DealScan. Finally, we identify 257 CBN deals in which the merging firms have outstanding loans that originated in bank syndicates headed by the same lead bank prior to the merger announcement.

First, we examine H1 by testing whether firms connected through a CBN are more likely to engage in a merger of high asset complementarity. Following Rhodes-Kropf and Robinson (2008), we adopt the absolute difference of the merging firms' pre-merger market-to-book ratios (henceforth, we refer to the measure as *Q-closeness*) as a proxy for the degree of asset complementarity between two firms.[5] Our first empirical results from a multivariate logit model on the matched samples show that firms with high asset complementarity, as indicated by a high Q-closeness between the firms, are more likely to strike a merger deal when the firms are connected through a CBN. This result is consistent with H1, suggesting that lower search costs allow network firms with complementary assets to meet and merge more easily.[6] Furthermore, additional tests reveal that the likelihood of complementary mergers increases with the number of target-like firms in the acquirers' bank networks. This result indicates that the CBN can reduce an acquirer's search costs only when the network can provide the acquirer with enough *plausible* candidate options to

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[5] Rhodes-Kropf and Robinson (2008) show that firms engaging in complementary mergers endogenously choose to merge with complementary partners of similar quality and that the financial market impounds the expectation for the outcome into the merging firms' pre-merger market-to-book ratio.

[6] Alternatively, the Q-theory of mergers (Jovanovic and Rousseau, 2002) implies that banks are more likely to use their private knowledge about the borrowers' financial situations to facilitate *substitute mergers*, in which high-quality firms merge with low-quality firms.

choose from. These findings further strengthen the model's prediction that the banks use their lending networks to reduce the constituents' search costs.

Next, we verify H2 by testing whether recently originated connections predict complementary mergers better and find evidence consistent with the prediction. This result suggests that banks facilitate complementary mergers only when the loans still have long maturity remaining and thereby an increase in uncertainty from a merger deal can have a significantly negative impact on the loan value.

We then test H3 to examine whether the mergers stemming from lower search costs owing to CBNs actually create superior synergistic values for the combined firm shareholders. To measure the value created by the mergers, we employ three-day cumulative abnormal returns computed using the Fama-French-Carhart (1997) four-factor model.[7] Our multivariate test on the actual mergers reveals that a merger between firms sharing a CBN is associated with increases of 1.49% and 1.20% in the announcement returns of the combined firms and the acquirers, respectively, in support of H3.[8] To check whether mergers stemming from low search costs have real effects beyond positive stock market reactions, we examine whether CBN mergers exhibit superior post-merger operating efficiency. A matched firm analysis confirms that the CBN mergers show a substantial improvement in long-term post-merger return on assets (ROA) and asset turnover compared to other deal types. These results, coupled with the previous results on announcement returns, provide strong and consistent support for H3, which states that merger deals stemming from lower search costs create superior synergistic value.

Additional results indicate that acquirers in the CBN deals tend to take a greater share of the merger benefits than the targets. Nevertheless, the targets are not worse off than those in non-CBN deals; these results are consistent with H4, which indicates that the banks' assistance reduces the acquirers' search costs more than the targets', thus benefitting the acquirers with increased bargaining power.

[7] The idea is that if the financial market only partially impounds the potential gain from future merger deals in the pre-merger market value of the merging firms due to uncertainty, we should observe additional price movement when the merger announcement actually takes place, thus reducing the uncertainty to zero.
[8] The use of alternative models such as the market model, three-factor model, and five-factor model yields qualitatively similar results

Finally, we explore the banks' participation conditions by testing H5, which proposes that the synergistic gain from CBN mergers is attained without a substantial increase in post-merger asset volatility. To test this prediction, we construct two alternative measures that capture the changes in the asset volatility of the merging firms over the pre- and post-merger periods using the Merton's (1974) approach. The results suggest that there is no systematic difference in the effect of mergers on the changes in total asset risk exposures between the CBN and non-CBN merger groups. Next, we directly test the effect of CBNs on the cost of bank loans using bank loan data taken from the pre- and post-merger periods. The results indicate that CBN deals are indeed associated with a reduction in post-merger borrowing costs. The evidence is consistent with the notion that banks facilitate mergers only when the deals improve the ability of merger participants to service their debt without introducing additional asset risk to banks, thereby increasing the value of banks' existing loan portfolios.

These results provide strong evidence consistent with the model's central implication: a reduction in search frictions increases the likelihood of mergers of greater complementarity and higher synergistic value. The key underlying assumption for the inference from the findings is that CBNs reduce search frictions. However, several alternative factors can potentially explain the baseline empirical results. First, other types of inter-firm networks, such as shared geographical or industry networks, could reduce search costs, and firms connected via these networks could also develop relationships with common banks. To test the confounding explanations, we perform our baseline tests including the controls for geographic proximity and the same industry factors. The baseline results are robust to the inclusion of these controls.

Second, the information environments surrounding the individual firms could comprehensively explain both the likelihood of having complementary mergers and CBN connections. That is, high-quality information environments could allow firms with complementary assets to consummate mergers more easily and have easier access to loan capital. To address the alternative explanation, we estimate the baseline models augmented with additional variables capturing the firms' state of information environments generated using factor analysis (Karpoff, Lee, and Masulis, 2013; Masulis and Simsir, 2018). The test results indicate that the explanatory power of the information variables on the likelihood of complementary mergers is weak in the presence of CBN. The results are inconsistent with the alternative explanation and suggest that CBN connections provide a broader range of channels for a reduction in search costs than the quality of the firms' information environments.

Third, the merging firms' access to a large bank and inclusion in its exclusive borrower network could be correlated with latent firm characteristics, such as high firm quality, instead of being correlated with having low search costs. To address this confounding explanation, we construct two comparator sets consisting of non-CBN mergers in which the bank and firm quality are comparable to those in the CBN mergers. Then, we estimate the baseline models using the sample consisting of only the CBN deals and non-CBN deals from the two comparator sets. The baseline results are robust to this alternative setting, thus confirming that our results are not driven by quality-related latent variables correlated with CBNs.

Overall, the findings of the study suggest that lower search costs allow firms with complementary assets to locate each other better and combine through mergers, thus facilitating a more efficient redistribution of control rights. With these findings, this study makes two major contributions to the mergers and acquisitions (M&A) and corporate banking literature. First, it contributes to the literature concerning the boundaries of the firm as formalized by Grossman and Hart (1986) and Hart and Moore (1990) and extended by Rhodes-Kropf and Robinson (2008) to the assortative matching theory of mergers. Building on Rhodes-Kropf and Robinson's findings using a network approach, our paper shows that, on average, a reduction in search frictions owing to the bank network connection facilitates mergers of asset complementarity rather than the substitute mergers implied by the Q-theory of mergers (Jovanovic and Rousseau, 2002). Furthermore, we present evidence that delineates the effects of search frictions from those of information opacity or latent firm characteristics on merger outcomes.[9] To the best of our knowledge, our paper is the first to theoretically and empirically highlight the importance of search as the determinant of matching quality and synergy in complementary mergers.[10]

[9] We thank the anonymous referee for suggesting the test.

[10] Although several papers investigate mergers between firms connected through shared networks, they do not focus on the effect of the networks on search frictions in complementary mergers. For example, Cai, Kim, Park, and White (2016) show that a common auditor helps merging firms reduce uncertainty throughout the acquisition process. Dhaliwal, Lamoreaux, Litov, and Neyland (2016) and Chang, Chander, Shekhar, Tam, and Yao (2016) focus on rent-seeking behavior of acquirers who have insider information of

Second, this study also contributes to the literature on how relationships with commercial banks through loan origination and renewal signal the quality of a borrowing firm and affect the firm's market value (e.g., Fama, 1985; Mikkelson and Partch, 1986; James, 1987; Lummer and McConnell, 1989; Bharadwaj and Shivdasani, 2003). By showing that mergers between firms that have common associations with a bank create synergistic value through reduced search costs, we highlight an alternative channel through which relationships with banks can increase firm value.

The remainder of the paper is organized as follows: Section 2 discusses a simple search and bargaining model and how the hypotheses are developed, Section 3 details the data construction, Section 4 presents the empirical findings, and Section 5 concludes the paper.

2. Search and bargaining model for mergers

2.1. Model setup

We consider a risk-neutral, infinite horizon economy with discount rate r. The economy features a random network that contains acquirers, N target candidates, and a bank, all with the objective of maximizing their respective shareholder values.[11] The bank has outstanding loans to the acquirers and also to a subset of the candidates consisting of $M \geq 0$ firms. Following the spirit of Rhodes-Kropf and Robinson (2008), we let the acquirers and target candidates be of types θ_A and θ_B, respectively, to capture asset complementarity between the firms; the smaller the absolute difference, $|\theta_A - \theta_B|$, the better the asset complementarity. Moreover, the acquirers' type $\theta_A \in \{0,1\}$ is binomial with probability mass $\pi(\theta_A)$, whereas the merger candidates' type $\theta_B \in [0,1]$ follows a uniform distribution, so $f(\theta_B) = 1$. Finally, θ_A and θ_B are unknown to the bank, whereas acquirers and targets, with their industry expertise, discover each

the targets through common auditor and advisor connections, respectively. Cai and Sevilir (2012) use common director connections between firms in merger deals as a channel for efficient information flow between firm officials. In the agency literature, Ishii and Xuan (2014) use the social connections among top officials of the acquirer and the target as a proxy for the agency problem. Ivashina, Nair, Saunders, Massoud, and Stover (2008) highlight shared bank networks as a channel for disciplinary mergers. None of the papers listed above provides evidence that the shared networks systematically reduce search frictions and facilitate synergistic complementary mergers. Finally, a contemporaneous study by Fee, Subramaniam, Wang, and Zhang (2019) also investigates the effect of common creditors on merger performance. While some of their empirical results are consistent with ours, our study is fundamentally different from Fee et al. in that ours is built on a search-and-bargain model rooted in the property rights theory whereas theirs is not. Besides, a direct comparison of the empirical results is not warranted; their sample includes financial firms and incomplete deals whereas we only include completed mergers between industrial firms following the literature on complementary mergers (Hoberg and Phillips, 2010; Bena and Li, 2014; Lee, Mauer and Xu, 2018).

[11] We discuss an alternative model setup featuring multiple banks in the economy in section 2.4.

other's type upon meeting. Assuming that the bank is not capable of identifying the firms' types is consistent with our focus on the acquirers' search through the bank's network. Indeed, it will be shown that the outcome of the model is *not* dependent on the bank knowing which particular acquirer-target candidate pair would generate the highest asset complementarity.[12] That is, the outcome will hold as long as the bank's assistance increases the acquirer's chance of accessing a large number of potential candidates through the bank's network.[13]

The merger brings in a synergy that depends on the asset complementarity of the acquirer and the target. The present value of the synergy at the merger announcement, which we note as $t = 0$, is $\mu(\theta_A, \theta_B) = \overline{\mu}(1 - |\theta_A - \theta_B|)$. The synergy is realized T periods after the merger and increases the firm value by $e^{rT}\mu(\theta_A, \theta_B)$. Figure 1 reports the proposed model timeline. Naturally, the firms have economic incentives to search for a merger partner with the highest asset complementarity possible to increase their post-merger shareholder value. Later, we introduce search frictions in the economy and examine the effect of the frictions on the matching quality. We then also study the role of bank lending networks mitigating the frictions and the participating conditions of the bank looking to protect the value of its existing loans.

We let the acquirer and target candidate's initial firm values be V_0^A and V_0^B, respectively.[14] If no merger occurs between the acquirer and the candidate, the values of the acquirer and the target at time $t = T$ are $V_T^A \sim N(e^{rT}V_0^A, e^{2rT}\sigma^2)$ and $V_T^B \sim N(e^{rT}V_0^B, e^{2rT}\sigma^2)$, respectively.[15] If a merger is consummated between them, then the value of the post-merger firm at time $t = T$ is $V^M \sim N(e^{rT}(V_0^A + V_0^B + \mu(\theta_A, \theta_B)), e^{2rT}\sigma'^2)$, and its asset volatility is σ'.[16] For brevity, the bank does not adjust the loan outstanding during the merger process. The acquirer's loan has a pre-merger value of D_0^A and a face value of $e^{rT}D_0^A$, and each of the target

[12] In this simple model setup, we make a conservative assumption that the bank is not capable of determining the firm types due to its lack of industry expertise. It can be shown that relaxing it to a weaker assumption that the bank receives noisy signals on the types actually strengthens the model's predictions.
[13] We empirically test this prediction in section 4.1.2 by examining the relation between the network size and the matching quality.
[14] To focus our analysis on the merger event, we do not model the continuous-time dynamics of firm value change.
[15] For simplicity, we assume the acquirer's and target's pre-merger asset volatilities are the same, σ. Our result remains valid even if the acquirer and target are assumed to have different pre-merger asset volatilities.
[16] Since the model result is driven by the volatility of post-merger firm assets, we choose not to explicitly model the correlation among the variations in the acquirer and target asset values.

candidates' loans have a pre-merger value of D_0^B and a face value of $e^{rT}D_0^B$. All loans mature at T, the same time as the realization of the merger synergy.

2.2. Merger network model: Acquirer's search and bargaining

We primarily focus on the acquirer-initiated search process on the basis of the findings in the literature that most merger deals are initiated by the acquirers (Masulis and Simsir, 2018).[17] Following the random network model in the classic network literature (Erdos and Renyi, 1959; Bollobas and Bela, 2001; Jackson, 2008), we assume that each acquirer searches for a target by forming random connections with each of the N candidates in the economy with probability p in each period. Although N is a large number, we let p represent a substantially low probability such that $Np < 1$.[18]

For an acquirer with an outstanding bank loan, the bank may choose to assist the acquirer's search effort if doing so benefits the bank.[19] We explore the bank's participating conditions in Section 2.3. *If the bank chooses to participate* in facilitating the merger, the bank searches through its lending network of M borrowers and solicits a target candidate from the network with a probability p' per period for the acquirer. Once the acquirer with type θ_A meets with a candidate, the acquirer observes the candidate's type as θ_B and decides whether or not to enter a Nash bargaining session, the outcome of which features the acquirer's share $s(\theta_A, \theta_B)$ of the merger synergy (Rubinstein 1982).[20] The acquirer's searching continues during the Nash bargaining session. Here, we make the following assertion first and then verify later.[21]

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[17] We discuss the target-initiated search process in Section 2.4.

[18] This setup reflects the reality that when there are a large number of possible target candidates, search frictions hinder firms' ability to find a proper merger candidate in a given time period. Indeed, Boone and Mulherin (2007) suggest that a typical merger deal is preceded by a long relationship-building period, during which the acquirer's management earns the trust of the candidate's top officials and also collect information of the candidate. We interpret p as being inversely related to the amount of time and efforts committed by the acquirer for each candidate.

[19] The legality of commercial banks' transmitting the borrowers' private information to potential acquirers was disputed in the following hostile takeover cases: TW Corp.-Washington Steel deal (Washington Steel Corp. v. TW Corp., U. S. Court of Appeals, Third Circuit; 602 F.2d 594); American Medicorp-Humana deal (Humana, Inc. v. American Medicorp, Inc., New York Southern District Court; FED. SEC. L. REP. (CCH) 96,286); Western Resources-ADT Operations deal (ADT Operations, Inc. v. Chase Manhattan Bank, Supreme Court, New York County; 173 Misc. 2d 959). The courts generally found the banks' use of the information in facilitating the takeover deals to be within the boundaries of the law. On the basis of these rulings, our model does not account for potential legal liabilities against banks for facilitating mergers.

[20] We acknowledge that, in reality, the acquirer and target share the merger synergy through various exchange mediums, such as cash vs. stocks (Hansen 1987). Nevertheless, as Hansen (1987) suggests, the choice of exchange medium is driven by information asymmetry, or the bargaining power due to information asymmetry. Because neither of these is the focus of our paper, we choose not to explicitly model the exchange medium but rather focus on the split of synergistic value.

[21] Kyle (1985) adopts a similar solution technique: a linear equilibrium is asserted first then proved.

Assertion 1: In equilibrium, $\mu(\theta_A, \theta_B)s(\theta_A, \theta_B)$ increases in the asset complementarity of the acquirer and target. In other words, $\mu(\theta_A, \theta_B)s(\theta_A, \theta_B)$ decreases in $|\theta_A - \theta_B|$.

Assertion 1 suggests that the portion of synergy, in dollars, retained by the acquirer increases in the level of asset complementarity with the target. Subsequently, the assertion indicates that an acquirer with θ_A sets a threshold level of $\theta_B^*(\theta_A)$ such that the acquirer enters the bargaining session only with candidates with good enough asset complementarity, that is, $|\theta_A - \theta_B| \leq |\theta_A - \theta_B^*(\theta_A)|$.

The threshold level of $\theta_B^*(\theta_A)$ also affects the bank's equilibrium decision of participation. Unlike the acquirer, commercial banks, whom we assume to lack the industry-specific knowledge, cannot discover the degree of asset complementarity between each pair of acquirer and target. Nevertheless, a rational bank does know the equilibrium threshold level of $\theta_B^*(\theta_A)$ varies with its decision of whether or not to assist the acquirer and will participate only if doing so increases the value of its loan portfolio. The bank's portfolio value $\Pi(\theta_B^*(\theta_A), \sigma')$ depends on the threshold $\theta_B^*(\theta_A)$ and post-merger asset volatility σ'. Intuitively, the post-merger asset volatility σ' plays an important role for the bank, who essentially faces the payoff schedule of a short European call option (Jensen and Meckling 1976). If the σ' is too high, then the bank might *not* be willing to have the firms in its lending network to be involved in the merger transaction. That is, the bank only facilitates the acquirer's search when the bank's participation leads to a new threshold, which we note as $\hat{\theta}_B^*(\theta_A)$, such that $\hat{\Pi}(\hat{\theta}_B^*(\theta_A), \sigma')$ increases in value. We then define the equilibrium in the merger network between the acquirer, targets, and the bank as follows.

Definition: The equilibrium of the acquirer and bank's strategy is the tuple $\left\{\theta_B^*(\theta_A), \hat{\theta}_B^*(\theta_A), s(\theta_A, \theta_B), \hat{s}(\theta_A, \theta_B), \Pi(\theta_B^*(\theta_A), \sigma'), \hat{\Pi}\left(\hat{\theta}_B^*(\theta_A), \sigma'\right)\right\}$ such that

- Without bank-facilitated searching, the acquirer with θ_A chooses the optimal bargaining threshold $\theta_B^*(\theta_A)$ such that she enters the bargaining session with any candidate with θ_B so that $|\theta_A - \theta_B| \leq |\theta_A - \theta_B^*(\theta_A)|$ and obtains $s(\theta_A, \theta_B)$ fraction of the synergy.

- With bank-facilitated searching, the acquirer θ_A chooses the optimal bargaining threshold $\hat{\theta}_B^*(\theta_A)$ such that she enters the bargaining session with any candidate with θ_B so that $|\theta_A - \theta_B| \leq |\theta_A - \hat{\theta}_B^*(\theta_A)|$ and obtains $\hat{s}(\theta_A, \theta_B)$ fraction of the synergy.
- The bank facilitates the acquirer's searching only if doing so increases its loan portfolio value, that is, $\hat{\Pi}(\hat{\theta}_B^*(\theta_A), \sigma') \geq \Pi(\theta_B^*(\theta_A), \sigma')$.

2.3. Equilibrium solution of merger network

We first illustrate the search and bargaining outcome in Lemmas 1 and 2. See Appendix E for full proof.

Lemma 1: The acquirer's searching in the random network leads to a Poisson sequence of target candidates, and the probability of meeting with n candidates in each time period is $f(n;\kappa) = \frac{e^{-1/\kappa}}{\kappa^n n!}$. The parameter κ is the average of the inter-arrival times of two candidates, where $\kappa = \frac{1}{Np+Mp\prime}$ when the bank assists the acquirer's search effort, and $\kappa = \frac{1}{Np}$ when it does not.

A higher κ corresponds to higher *search costs*: an acquirer has to spend more time and resources searching within the network to access a new candidate. Lemma 1 shows that commercial banks, which can reduce search costs, can help an acquirer access the candidates more efficiently. We are now ready to fully characterize the equilibrium.

Proposition 1: Without bank-facilitated searching, the acquirer's search cost is $\kappa = \frac{1}{Np}$, whereas the equilibrium threshold $\theta_B^*(\theta_A)$ and bargaining outcome $s(\theta_A, \theta_B)$ are

$$\theta_B^*(0) = \theta_B^* = 1 - \overline{\mu} \sum_{n=1}^{+\infty} c_n \left[\frac{2\kappa - 1}{4r\kappa^2\overline{\mu} - 2(1-2\kappa)}\right]^{2n-1}, and\ \theta_B^*(1) = 1 - \theta_B^*, \tag{1}$$

$$s(\theta_A, \theta_B) = \frac{1}{2} + \frac{1}{2(1-|\theta_A - \theta_B|)} \sum_{n=1}^{+\infty} c_n \frac{\overline{\mu}(2\kappa-1)^{2n-2}}{[4r\kappa^2\overline{\mu} - 2(1-2\kappa)]^{2n-1}}. \tag{2}$$

With bank-facilitated searching, the acquirer's search cost is $\hat{\kappa} = \frac{1}{Np+Mp\prime} < \kappa = \frac{1}{Np}$, whereas the equilibrium threshold $\hat{\theta}_B^*(\theta_A)$ and bargaining outcome $\hat{s}(\theta_A, \theta_B)$ are

$$\hat{\theta}_B^*(0) = \hat{\theta}_B^* = 1 - \overline{\mu}\sum_{n=1}^{+\infty} c_n \left[\frac{2\hat{\kappa}-1}{4r\hat{\kappa}^2\overline{\mu}-2(1-2\hat{\kappa})}\right]^{2n-1}, and\ \hat{\theta}_B^*(1) = 1 - \hat{\theta}_B^*, \tag{3}$$

$$\hat{s}(\theta_A, \theta_B) = \frac{1}{2} + \frac{1}{2(1-|\theta_A-\theta_B|)}\sum_{n=1}^{+\infty} c_n \frac{\overline{\mu}(2\hat{\kappa}-1)^{2n-2}}{[4r\hat{\kappa}^2\overline{\mu}-2(1-2\hat{\kappa})]^{2n-1}}. \tag{4}$$

The bank is willing to facilitate the merger only when $\sigma' \leq \hat{\sigma}^*$, where $\hat{\sigma}^*$ satisfies the condition $\hat{\Pi}\left(\hat{\theta}_B^*(\theta_A), \hat{\sigma}^*\right) = \Pi(\theta_B^*(\theta_A), \hat{\sigma}^*)$, or equivalently,

$$0 = \int_{\hat{\theta}_B^*}^{\theta_B^*} \overline{\mu}(1-\theta_B)\Phi(-\delta') - \frac{\sqrt{T}}{\sqrt{2\pi}}\sigma' e^{-rT-\frac{\delta'^2}{2}} + \sum_{i\in\{A,B\}}\left[D_0^i - V_0^i\right]\left[\Phi(\delta') - \Phi\left(\delta^i\right)\right] + \frac{\sqrt{T}}{\sqrt{2\pi}}\sigma e^{-rT-\frac{\delta^{i2}}{2}} d\theta_B\,, \tag{5}$$

where $\delta^A = \frac{e^{rT}(V_0^A - D_0^A)}{\sigma\sqrt{T}}$, $\delta^B = \frac{e^{rT}(V_0^B - D_0^B)}{\sigma\sqrt{T}}$, and $\delta' = \frac{e^{rT}(V_0^A + V_0^B - D_0^A - D_0^B + \mu(\theta_A, \theta_B))}{\sigma'\sqrt{T}}$.

Proposition 1 supports Assertion 1 by showing that the acquirer retains more synergy from bargaining with a candidate having better asset complementarity with the acquirer. Note that the model's implication on $s(\theta_A, \theta_B)$ remains intact even if the candidate has a positive outside option as long as *p* is small.

2.4. Comparative statics and hypothesis development

Next, we compare the equilibrium outcome of the bank-facilitated merger process and that of the baseline merger process to determine the extent to which the commercial lending network affects the merger outcome by facilitating the search process.

Proposition 2: The average asset complementarity in mergers is higher when the acquirer and target are connected through a common bank. Moreover, the effect is stronger when the bank's lending network size M or bank network search efficiency p' increases.[22]

Proposition 2 allows us to hypothesize the relation between CBNs and merger performance in the context of Rhodes-Kropf and Robinson (2008). Specifically, our equilibrium results suggest that an acquirer merges with a candidate when their respective types (i.e., θ_A and θ_B) are close enough. This result is

[22] Although we do not explicitly model the effect of search frictions on the search results of the acquirers that do not have a relationship with the bank, we can emulate the effect by setting *M*=0 in Proposition 2. In such a case, the equilibrium thresholds $\hat{\theta}_B^*(0)$ and $\hat{\theta}_B^*(1)$ degenerate to $\theta_B^*(0)$ and $\theta_B^*(1)$, respectively.

consistent with the like-buys-like mergers in Rhodes-Kropf and Robinson (2008). They show that firms endogenously choose to merge with complementary partners of similar quality and that the financial market impounds the expectation for the outcome into the merging firms' pre-merger market-to-book ratio. Then, by using the absolute difference of the market-to-book ratio between the merging firms as a proxy for the firm types, as in Rhodes-Kropf and Robinson (2008), we can test the following hypothesis and check the validity of our mechanism.

H1: Firms connected through a CBN are more likely to engage in a complementary merger than firms not connected through such a network.

Proposition 2 also implies that the likelihood of high asset complementarity mergers increases with the size of the likely target candidate pool in the common bank's lending network.

H1 stems from the model implication that the bank facilitates mergers between borrowers by reducing search costs when doing so helps the bank protect the value of the loans extended to the borrowers from poor quality mergers. This prediction implies that if a merger is not likely to affect loan values, the bank's incentive to facilitate a better merger is weakened. For example, if an outstanding loan for a borrower is scheduled to mature shortly after the completion of a merger, then the bank would have little interest in assisting the firm because the value effect of helping the firm will be trivial, especially if the bank must incur a non-zero cost to reduce search frictions. This observation leads to the next prediction.

H2: The search friction-reducing effect of a CBN is more pronounced when the connection is made of recently originated loans than when it is made of old or expired loans.

Next, the higher average merger synergy shown in Proposition 2 will be reflected in a better merger announcement return. Hence, Proposition 2 also implies the following hypothesis:

H3: Mergers between firms connected through a CBN create greater synergistic value.

We now turn our attention to how the synergy is allocated between the acquirer and the target.

Proposition 3: The acquirer obtains a higher equilibrium share of synergy when the acquirer and target are connected through a common bank network, that is, $\hat{s}(\theta_A, \theta_B) > s(\theta_A, \theta_B)$.

Proposition 3 suggests the acquirer's bargaining power becomes stronger with the common bank relationship, which gives us the following hypothesis.

H4: Acquirers retain a greater share of merger synergy than targets in CBN mergers.

Finally, Proposition 1 also suggests that a CBN merger is not associated with a relatively higher post-merger volatility.

H5: Greater synergistic value of CBN mergers is achieved without substantially increasing the asset volatility of the combined firms.

H5 as well as H2 concern the bank's incentives and participation constraints implied from the model. Combined with CBN mergers' association with superior synergy, these predictions imply an increase in the outstanding loan portfolio value for the bank facilitating CBN mergers.

These predictions are based on the model assumption that the search for merger partners is initiated by acquirers. However, it can also be shown that similar implications are derived even if we construct the model focusing on target-initiated search, especially when the targets are financially distressed and desperate for liquidity. Consider two financially distressed firms that are in a demand shock seeking financial relief through acquisition by liquidity-rich firms. The bank, who has economic incentives to protect its outstanding loans in the firms, assists in their search for acquirers by giving them access to other firms in the network. An acquirer approached by the two distressed firms through the network compares the level of asset complementarity between itself and each of the two firms and then makes an offer to the one with greater complementarity. The selected target's shareholders face an increasingly large opportunity cost of not taking the offer from the acquirer and are incapable of turning the bank's assistance into bargaining leverage. Due to the target's weak bargaining position, the acquirer takes a greater relative share of the synergy gain. Indeed, Masulis and Simsir (2018) show that the majority of the deals are initiated by acquirers and that the target-initiated deals overwhelmingly involve targets in severe financial distress. From these findings, we argue that whether a deal is initiated by an acquirer or a target has little empirical relevance for our study. Since the deals are mostly acquirer-initiated, we focus on acquirer-initiated search.

Lastly, our analysis so far is based on a simple model with a single-bank lending network. How would the predictions we derive using our one-bank setting carry over to more realistic scenarios in which multiple banks connected to an acquirer form an aggregate lending network? We acknowledge that the analysis based on multi-bank networks could involve an additional layer of a strategic game among the banks on participation choices; this prediction is neither of a first-order effect nor within the scope of our study. We assert that, holding other factors constant, the search cost faced by the acquirer will be generally lower when there are more potential target candidates in the aggregate lending network and that all of the predictions we derived will hold in the multi-bank cases. We put these predictions to the test in the next two sections to verify whether the data support our main proposition that lending networks reduce search frictions for firms seeking complementary merger partners.

3. Data construction

In this section, we discuss the data construction process and the key explanatory variables of the paper.

3.1. Baseline data set construction

We combine the following four databases for our empirical analysis: information concerning the sample mergers from the SDC database, merger participants' CBN relationships from DealScan, and firm-specific characteristics and daily stock returns from Compustat and the Center for Research in Security Prices (CRSP). We begin with all completed merger deals in the SDC database during the sample period 1992–2016. Repurchases, recapitalizations, minority-share purchases, exchange offers, spin-offs, and privatizations are excluded from the sample. Deals in which the ratio of the deal value to the market value of the acquirer is less than 1%, deals with toeholds greater than 50%, and deals with a post-deal share ownership less than 100% are excluded. We also remove deals involving firms in the financial and utility sectors (SIC in 6000s and 4949-4999s) because of the concern that government regulations can potentially affect shareholders' or management's incentives surrounding merger transactions.

All the acquirers and the targets in the sample are publicly traded firms listed on the NYSE, Nasdaq, or Amex; are headquartered in the U.S.; have CRSP share code 10 or 11; and have non-missing daily CRSP stock return data and annual Compustat data for at least one year prior to the merger announcement. We combine the SDC data set with the Compustat and CRSP data to construct our initial sample of 1,683 completed merger deals. We then combine the initial merger sample with the DealScan data to identify lending relationships between the sample firms and the lending institutions in DealScan for the period preceding the merger announcement.[23] Carey and Hrycray (1999) show that the coverage of the DealScan data begins to improve in the early 1990s, and we establish 1992 as the first year of our sample period.[24] The online Appendix B reports in detail how the data screening process is conducted.

3.2. Key explanatory measure and descriptive statistics

The main prediction of our paper is that low search costs induced by a CBN facilitate value-creating complementary mergers. The literature concerning the loan syndicate structure shows that a lead bank in a syndicated loan performs both screening and monitoring roles in loan performance; these roles allow the lead bank greater access to the top personnel and private information of a borrower than other participants of the loan (Ivashina, 2009; Lin, Ma, Malatesta, and Xuan, 2012). Therefore, we predict that the effect on shareholder value creation is strongest when the common bank serves as the lead bank for loan facilities made to both the acquirer and the target. Based on this prediction, we construct CBN (the key explanatory variable throughout this paper) to indicate whether two firms are connected through a common bank lending network. We introduce CBN as a binary variable that takes a value of 1 if the following two conditions are met and 0 otherwise: (i) two firms have loan facilities originating in bank syndicates headed by the same lead bank at some time prior to the merger announcement, and (ii) both firms' loan facilities from the common bank are not expired at the time of the merger announcement. We define a bank as a lead bank if DealScan assigns lead arranger or lead agent credits to the bank.[25]

[23] We use the DealScan-Compustat linking table created by Chava and Roberts (2008). Since their linking table ends in 2012, we supplement it with manual data collection to extend our sample to 2015.
[24] Carey and Hrycray (1999) claim that the DealScan coverage reaches 90% of all commercial loan value after 1995. Changing the first year of the sample period to 1995 does not change our baseline result in any material way.
[25] We estimate the empirical models of this paper using an alternative CBN measure constructed using a common bank connection through non-lead banks. The coefficients on the alternative CBN measure are insignificant across most of the model specifications (results not tabulated). We argue that this is because lead banks have stronger incentives and means of collecting private information on their borrowers than other syndicate participants (Ivashina, 2009).

Panel A of Table 1 reports the descriptive statistics of the acquirers, the targets, and the deal-specific characteristics in our 1,683 sample merger deals. Consistent with the literature, the acquirers tend to be larger, older, more profitable, and with a slightly higher Q than the target firms, whereas the target firms have a greater research and development (R&D) ratio than the acquirers. The acquirers also have more outstanding bank loans and institutional equity ownership than the target firms.

Panel B of Table 1 reports the annual distributions of the sample merger deals (Column 1) and CBN deals (Column 2). Because the DealScan data period begins in the late 1980s, the later years in our sample period tend to see more of those deals in which the merging firms have CBNs. To address the potential mechanical relationship, we focus on a subsample of CBN deals in which the common bank has served as a lead bank for both the acquirer and the target on outstanding loan facilities that originated *within the four-year period* prior to the merger announcement.[26] We refer to the subgroup of CBN deals as *CBN_Recent* and report the annual deal distribution in Column 3. Even with CBN_Recent, the annual ratios of CBN deals to the total sample deals exhibit an upward trend.

4. Empirical results

In this section, we investigate the importance of search in the merger process by testing the model's empirical predictions.

4.1. Search costs and the likelihood of complementary mergers

We begin the section by examining the main prediction of the model, H1: firms connected by a CBN are more likely to engage in a complementary merger due to low search costs. To test the prediction, we take an empirical strategy of comparing actual mergers to hypothetical mergers. First, we construct control samples of hypothetical merger deals (i.e., untreated sample) for the 1,683 actual merger deals in our baseline data set (i.e., treated sample) using the following two matching techniques: (i) nearest-neighbor matching, which we label matching technique 1, and (ii) propensity score matching, which we label matching technique 2. For matching technique 1 (2), each acquirer-target pair of an actual deal announced

[26] The average time to maturity of bank loans at loan origination in the DealScan database during our sample period is about four years, which is our basis for using four years as the cut-off point in classifying recently formed common bank lending relationships.

in year y is matched with up to five pairs of non-merger Compustat firms from year y-1 and the same industry using a Mahalanobis distance model (a logit model) by asset size, one-year past return, and the number of outstanding bank loan facilities. The non-merger control firms are selected from a pool of industrial firms that did not acquire any firms in completed merger deals during the [y-2, y] period prior to the merger announcement year y. Industries are matched by the most granular Standard Industrial Classification (SIC) grouping possible that gives up to five control firms.

Before we test H1, we first test whether a high level of asset complementarity between any two firms is associated with a greater likelihood of a merger occurring between them. In so doing, we follow Rhodes-Kropf and Robinson (2008) and construct the measure $|AcqQ - TarQ|$, which captures the extent of asset complementarity between the firm pairs. The measure is designed to gauge the difference in the market-to-book ratio between the two firms in a deal and is constructed by taking the absolute value of the difference in the log-transformed market-to-book assets of the firms. Then, we convert it into a measure of closeness (i.e., Q-closeness) by multiplying it by -1. To test the initial prediction, we estimate the following logit model constructed in the spirit of Bena and Li (2012):

$$[Acquirer - Target]_{Treated} = \Lambda(\beta_1(-|AcqQ - TarQ|) + \theta_1 Acquirer\ characteristics_{t-1} + \theta_2 Target\ characteristics_{t-1} + year + \varepsilon), \tag{6}$$

where $[Acquirer - Target]_{Treated}$ is a binary variable that takes the value of 1 if the acquirer-target pair is one of the actual 1,683 treated pairs from the SDC merger database and 0 if the pair is from the matched control deals. The control variables consist of factors known in the M&A literature to be correlated with the likelihood of firms becoming merger participants (e.g., Bena and Li, 2014; Lee, Mauer, and Xu, 2018), including asset size, Q, one-year past returns, leverage, ROA, cash holdings, firm age, and the institutional ownership of the firms. All control variables are measured at the beginning of the fiscal year in which the treated merger announcement occurs.

We report the logit regression results in Columns 1 and 4 of Table 2. The coefficient estimates on the measure of Q-closeness, $-|AcqQ - TarQ|$, in both models are positive and statistically significant. This result is consistent with the prediction by Rhodes-Kropf and Robinson (2008) that a high degree of asset complementarity between two firms is associated with a greater likelihood of a merger between the two firms. The estimates of the other coefficients are closely comparable to the findings in the literature (e.g., Bena and Li, 2014; Lee, Mauer, and Xu, 2018). Furthermore, the number of acquirers' (targets') outstanding loans is positively (negatively) associated with the merger likelihood. These estimates are consistent with the notion that firms with easy access to external financing are likely to acquire financially constrained targets (Almeida, Campello, and Hackbarth, 2011).

Next, we test the full prediction of H1. In so doing, we estimate the baseline Eq. (7), a modified version of Eq. (6) that includes CBN and its interaction term with the Q-closeness variable, $-|AcqQ - TarQ|$. Note also that the firm pairs in the non-merger control sample can also be connected through CBNs as well.[27]

$$[Acquirer - Target]_{Treated} = \Lambda(\gamma_1 CBN \times (-|AcqQ - TarQ|) + \gamma_2(-|AcqQ - TarQ|) + \gamma_3 CBN + \theta_1 Acq\_tar\ distance_{t-1} \times (-|AcqQ - TarQ|) + \theta_2 Same\ industry_{t-1} \times (-|AcqQ - TarQ|) + \theta_3 Acquirer\ characteristics_{t-1} + \theta_4 Target\ characteristics_{t-1} + \varepsilon). \quad (7)$$

H1 predicts that γ_1 is positive. Columns 2 and 5 of Table 2 report the estimation results. The stand-alone Q-closeness measure $-|AcqQ - TarQ|$ continues to be positively and significantly associated with the merger likelihood. Most importantly, the coefficients of $CBN \times (-|AcqQ - TarQ|)$ are large and positive, suggesting that low search costs due to a CBN help firms with complementary assets to locate each other and strike merger deals. These estimates are consistent with the prediction in H1. Note that the Q-theory of mergers (Jovanovic and Rousseau, 2002) implies that if the banks use their private knowledge on the borrowers' financial situations to facilitate mergers among network constituents, they will more likely facilitate substitute mergers in which high-quality firms acquire low-quality firms. Our results are inconsistent with the prediction implied by the Q-theory of mergers.

4.1.1. CBN connections formed recently versus in the distant past

Next, we test H2, which predicts that CBNs based on recently originated loans rather than loans that originated in the distant past are more effective in reducing search costs. The idea is that the banks'

[27] There are 872 (808) CBN-connected firm pairs in the non-merger control sample constructed using matching technique 1 (technique 2).

economic incentive to facilitate mergers is strong when the loans extended to the firms searching for merger partners have substantial time left toward maturity; thus, assisting them can significantly improve the value of the loans. Another way of interpreting the prediction is that the bank loans that are more recently originated hold more up-to-date information about the network constituents (Murfin, 2012). These interpretations are not mutually exclusive. To test this prediction, we employ the following two alternative measures of CBN variables: CBN_Recent, as introduced in Panel B of Table 1, and CBN_Old, a binary variable for CBNs that is formed in the previous period that ends four years (i.e., 1,460 days) before the merger announcement.[28] Our model predicts that CBN_Recent has a greater predictive power for complementarity mergers. Columns 3 and 6 in Panel A of Table 2 report the estimation results from the logit regressions of Eq. (7) using the alternative CBN variables. Compared to the coefficients on $-|AcqQ - TarQ| \times CBN$ in Columns 2 and 5, the coefficients on $-|AcqQ - TarQ| \times CBN\_Recent$ exhibit greater sensitivity, while those on $-|AcqQ - TarQ| \times CBN\_Old$ are insignificant. This result is consistent with H2. Later in Section 4.3.2, we further discuss the predictions in H2 when we examine the predictability of merger outcomes by CBN connections based on expired loans.

An obvious confounding explanation for the results so far is that other types of inter-firm networks, such as shared geographical or industry networks, can reduce search costs (Martos-Vila and Papakonstantinou, 2008), and the firms connected via these networks could also tend to have relationships with common banks. Note that Eq. (7) includes the two additional interaction terms of the Q-closeness measure, $Acq\_tar\ distance_{t-1} \times (-|AcqQ - TarQ|)$ and $Same\ industry_{t-1} \times (-|AcqQ - TarQ|)$, which address the geographic proximity and same industry factors. If a reduction in search costs is driven mostly by the common regional or industry network affiliations, and not by affiliations to a CBN, then these additional variables should subsume the explanatory power of $CBN \times (-|AcqQ - TarQ|)$. $Acq\_tar\ distance_{t-1} \times (-|AcqQ - TarQ|)$ exhibits insignificant and inconsistent estimates in Columns

[28] Untabulated results show that the average remaining time to maturity for the loans constituting the *CBN_Recent* deals, measured at merger announcement, is 35 months whereas that for the loans constituting the *CBN_Old* deals is only 20 months. Similarly, the average ratio of remaining maturity to the initial maturity for the loans constituting the *CBN_Recent* deals is 56% whereas that for the loans constituting the *CBN_Old* deals is only 30%.

2, 3, 5, and 6 in Panel A of Table 2. The coefficients on $Same\ industry_{t-1} \times (-|AcqQ - TarQ|)$ in the columns are all positive, consistent with the notion that firms with common industry affiliation face low search costs. However, the fact that $CBN \times (-|AcqQ - TarQ|)$ still has significant explanatory power rejects the confounding explanation.

4.1.2. Search costs and bank network size

In this subsection, we further investigate the mechanism through which a CBN reduces search costs for its network constituents. The central prediction of our economic model is that bank networks reduce search costs for the bidder in search of a suitable merger partner by providing access to other network constituents as target candidates. From this idea, another prediction naturally emerges: if the search process is indeed made more efficient by providing easy access to the network constituents, the search efficiency must increase with the size of the network. Particularly, the greater the number of *plausible* target candidates the network presents to the acquirer (i.e., an increase in the arrival frequency of such candidates), the more likely the acquirer's search will lead to finding a complementary candidate among them. For example, a bank network will be more effective in reducing search costs for a biotech firm looking to buy a chemical firm if the bank can feed many chemical firms as candidate options to the acquirer. Figure 2 illustrates the central idea of the prediction.

To test the prediction, we construct two empirical measures for an acquirer's bank network size. The first measure, *AcqBankNetwork-All borrowers*, captures the size of the entire aggregate lending networks of the acquirer's banks. Specifically, the measure is a log-transformed count variable that equals the total number of all unique borrowers with outstanding loans from loan syndicates led by the same lead banks with whom the acquirer has outstanding loans. The second network measure, *AcqBankNetwork-Target peers,* captures the size of *the plausible target candidate pool* in the lending network of the acquirers' banks. The measure is the same count variable as *AcqBankNetwork-All borrowers* except that we only account for the borrowers that are operating in the same sector (i.e., having the same two-digit SIC code) and are of a similar size (i.e., the difference in their market equity being less than 10%) as the target firms in the deals. In constructing these measures, we subtract 1 from either measure if the firm pair in the deal has a CBN connection to remove redundant information. Then, we estimate the following logit model with the triple-interaction term involving CBN, Q-closeness, and the acquirer's bank network size:

$$[Acquirer - Target]_{Treated} = \Lambda(\gamma_1 CBN \times (-|AcqQ - TarQ|) \times AcqBankNetwork + \gamma_2(-|AcqQ - TarQ|) \times AcqBankNetwork + \gamma_3 CBN \times (-|AcqQ - TarQ|) + \gamma_4 CBN \times AcqBankNetwork + \gamma_5(-|AcqQ - TarQ|) \times CBN + \gamma_6 CBN + \gamma_7 AcqBankNetwork + \theta_1 Acquirer\ characteristics_{t-1} + \theta_2 Target\ characteristics_{t-1} + \theta_3 Same\ state_{t-1} + \theta_4 Same\ industry_{t-1} + \varepsilon). \quad (8)$$

In estimating the model, we employ the two alternative measures, *AcqBankNetwork-All borrowers* and *AcqBankNetwork-Target peers*, for *AcqBankNetwork.* The empirical prediction is that γ_1 on the triple-interaction term is positive for both measures of bank network size, and the economic and statistical magnitude of γ_1 is greater when *AcqBankNetwork-Target peers* is used than it is when *AcqBankNetwork-All borrowers* is used.

Table 3 reports the estimation results for Eq. (8). First, Columns 1 and 4 report the results using *AcqBankNetwork-All borrowers* as the measure of bank network size, and the coefficients on the triple interaction term are positive but statistically insignificant. Next, we estimate the same model but use *AcqBankNetwork-Target peers* and report the results in Columns 2 and 5. The coefficients on the triple interaction term are positive and statistically highly significant at the conventional levels, indicating that the effect of a CBN on search efficiency is more pronounced when the size of the target-like firm pool in the bank network is large. Furthermore, note that the coefficients on $-|AcqQ - TarQ| \times CBN\_Recent$, which are significant in Table 2, are now all insignificant. This result reveals that the ability of the common network to reduce search frictions *entirely* relies on having enough plausible candidate firms. Together, the results are consistent with the prediction that CBNs reduce search costs precisely by providing the acquirers with many *plausible target options to compare and choose from.*

There are several possible confounding factors for the results documented in Columns 2 and 5 of Table 3 and we address these issues by estimating Eq. (8) augmented with additional controls. Columns 3 and 6 report the estimation results. First, the size of the plausible target candidate pool in the economy could be correlated with the size of the candidate pool in the bank network, and it is the former that is driving the results. To check this possibility, we include $TarIndustryPeers$, which is a log-transformed count variable that equals the total number of the target industry peers and its interaction term with $-|AcqQ - TarQ|$. The coefficients on both variables shown in the columns are all significantly negative, inconsistent with the alternative explanation.[29] Next, certain latent firm characteristics could be correlated with the frequency of loan originations from a specialized bank and also with a high probability of mergers.[30] Then, the inclusion of the interaction terms $-|AcqQ - TarQ| \times Acq\ outstanding\ loans$ and $-|AcqQ - TarQ| \times Tar\ outstanding\ loans$ in the model should subsume the explanatory power of the triple interaction term. The coefficients on the interaction terms are mostly statistically insignificant (3 out of 4 cases). Despite the inclusion of an array of the additional controls, the coefficients on the triple interaction term reported in Columns 3 and 6 exhibit an *increase* in their explanatory power compared to those in Columns 2 and 4. Collectively, the evidence in Table 3 confirms our earlier findings in Table 2 that low search costs enabled by CBNs allow acquirers to enjoy an efficient search process, which is more likely to result in a better-quality match.[31]

So far, we have examined how CBNs help reduce search costs for firms in the merger market and facilitate mergers of superior matching quality. In the next section, we investigate, by using the event study framework, whether CBN mergers are actually associated with synergistic value creation for the merging firms' shareholders.

4.2. Search costs and merger announcement return

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[29] The negative coefficients are consistent with the equilibrium outcome of our model. A larger *N* corresponds to a lower search cost κ, which induces the acquirer to be more selective and thus leads to a lower likelihood of merger between a particular acquirer-target pair. Moreover, when *N* increases, the probability of the candidates in either types (i.e., the candidates with high asset complementarity or the candidates with low asset complementarity) merging with the acquirer approaches zero, even though the former group of candidates starts with a higher likelihood.

[30] We explore this alternative explanation more extensively in section 4.3.

[31] We briefly discuss the potential effect of the lending network of the targets' banks on merger quality. We estimate Eq. (8), but this time using *TarBankNetwork*, which accounts for the targets' banks network size (reported in the Online Appendix C). The triple interaction term for both *TarBankNetwork-All borrowers* and *TarBankNetwork-Acquirer peers* are all positive but insignificant; this is consistent with the earlier discussions that banks are more incentivized to assist in the acquirers' search than targets' search for complementary merger partners.

In this section, we test H3 by investigating the consequence of pre-merger low search costs on the post-merger shareholder value. To do this, we employ the event study approach on the 1,683 actual merger deals as our empirical strategy. The underlying assumption is that the financial market only partially impounds the potential gain from future merger deals in the pre-merger market value, and the remaining value is impounded when the actual merger announcement occurs. Our primary measures of shareholder value gain created from mergers are the three-day cumulative abnormal returns [-1, +1] surrounding merger announcement dates [0]. The abnormal return is estimated by using the Fama-French-Carhart (1997) four-factor model, as follows: the estimation window is set as (-250, -7) trading days relative to the announcement day, with a minimum requirement of 100 days of non-missing CRSP stock returns and observations for the value-weighted market, size, book-to-market, and momentum factors. We first construct the announcement return measures first for acquirers (i.e., $AcqCAR3$) and targets (i.e., $TarCAR3$). Then we follow previous studies on M&A outcomes (e.g., Bradley, Desai, and Kim, 1988; Harford, Jenter, and Li, 2011; Cai and Sevilir, 2012) to define the combined announcement return as the weighted average cumulative abnormal return (i.e., $CombCAR3$) of the firms using the following formula:

$$CombCAR3 = \frac{AcqME \times AcqCAR3 + TarME \times TarCAR3}{AcqME + TarME}, \tag{9}$$

where $AcqME$ and $TarME$ are the market equity of the acquirer and the target, respectively, measured 10 trading days before the announcement date, with $TarME$ adjusted for the acquirer's toehold. We estimate the following baseline ordinary least squares (OLS) model on the sample of the 1,683 completed merger deals:

$$Announcement\ return_t = \beta CBN + X_{t-1}B_{t-1} + FE + \varepsilon_t, \tag{10}$$

where $Announcement\ return$ is proxied using $CombCAR3$. As in the previous tests, the key explanatory variable is CBN, which indicates that a deal is a completed merger between firms connected by a CBN.[32] H3 predicts β to be positive. In addition to CBN, the model includes a vector (i.e., X_{t-1}) of controls measured

[32] Note the subtle difference between CBN used for the models in Tables 2 and 3, which signifies firm pairs with common bank relationships that may or may not turn into a merger, and CBN for the models in Table 4, which signifies firm pairs with common bank relationships in completed merger deals.

at the beginning of the fiscal year of the deal announcement for firm and deal characteristics, which the M&A literature identifies to be associated with shareholder returns (e.g., Moeller, Schlingemann, and Stulz, 2004; Bargeron, Schlingemann, Stulz, and Zutter, 2008). The definitions for the control variables are provided in Appendix A.

Another potential confounding factor to be controlled for is that CBNs is correlated with the existence of common investment bank (IB) M&A advisors and that these common IB advisors could drive the results. To test this possibility, we first collect the IB financial advisor data from SDC and compare the IB advisors of the acquirer and the target for each deal to check whether there are deals where the firms share the same IB M&A advisors. Only three such cases exist in the entire sample and they are too few to have a meaningful explanatory power for the baseline results.[33] Next, to check whether CBN connections simply reflect acquirers employing targets' past IB advisors, we identify the sample M&A deals in which the acquirers' current IB advisors overlap with the targets' past IB advisors hired for M&A and equity issuance deals any time prior to the merger announcement. We find that there are 63 such cases, and we construct a binary variable Common IB that takes the value of 1 for the 63 cases and 0 otherwise.

Column 1 of Table 4 reports the estimation results. CBN is positively and significantly associated with the combined announcement return; this coefficient is consistent with H3, which predicts the superior combined return from mergers facilitated by low search costs. For example, the estimate of CBN indicates that a merger between firms connected by a CBN is associated with a 1.49% increase in the combined announcement abnormal return ($CombCAR3$). Considering that the unconditional mean of the combined abnormal return is 2.02%, the economic magnitude of the result is substantial. The control variables for horizontal deals (i.e., $Same\ industry$), deals with close proximity (i.e., $Acq\_tar\ distance$), and deals

[33] Agrawal, Cooper, Lian, and Wang (2013) investigate the effect of merging firms' hiring the same IB deal advisors on merger performance using a sample of 6,272 merger deals involving public acquirers and either public or private targets. Out of the 6,272 sample deals, they identify 98 deals as having the same advisors. We suspect that the discrepancy between their same advisor deal count (98) and ours (3) exists largely for two reasons. First, our sample does not include deals involving financial and utility firms, whereas their sample includes both. Indeed, Table 2 in their paper reports that 41 out of the 98 deals involve targets and acquirers each from the two industries, indicating that, at least 60% of the deals with the same advisor involve firms from other industries. Second, our sample includes only the public-public deals. Dropping the private target deals from their sample would substantially reduce the number of deals featuring the same advisors.

with investment banking ties (i.e., $Common\,IB$) are all insignificant, indicating that the association between CBN and the announcement return is not just a byproduct of common locality, common industry, or common IB relationships. The estimates on the other control variables are also broadly consistent with the results found in the literature.

Next, we examine H4, which predicts that an acquirer retains a greater share of merger synergy if the acquirer and the target are connected through a CBN. Testing the prediction requires a measure of relative value gain by the acquirers. Ideally, the relative gain of the acquirer should be measured by dividing the acquirer's dollar gain from a merger by the total dollar value of synergy. However, because the merging firms can have negative announcement returns, this approach of estimating acquirer gain can produce nonsensical values.[34] Therefore, following Ahern (2012) and Cai and Sevilir (2012), we estimate the acquirer's relative value gain over the three-day period surrounding the merger announcement date ($AcqGain3$) by using the following formula:

$$AcqGain3 = \frac{Acq.ME \times Acq.CAR3 - Tar.ME \times Tar.CAR3}{Acq.ME + Tar.ME}. \tag{11}$$

To test the prediction in H4, we estimate the same Eq. (10) separately for the acquirers and the targets using $AcqCAR3$ and $TarCAR3$, and then for the acquirer's relative gain to that of the target's by using $AcqGain3$. Columns 2-4 of Table 4 report the estimates. In Column 2, the estimates of CBN are positive and statistically significant, suggesting that the CBN predicts acquirers' increased return, with an average increase of 1.20%. The coefficient of CBN in Column 3 indicates that targets in the CBN deals are not worse off compared to targets in non-CBN deals. Together with the results in Columns 2 and 3, the positive and significant coefficient of CBN in Column 4 is consistent with the prediction in H4 that the extra synergy gain from bank network-facilitated efficient search is mostly accrued to the acquirers.

Additionally, we test if CBNs based on recently originated loans rather than loans originated a long time ago are predictive of greater merger synergy. To test this, we employ the two alternative measures of CBN

[34] As Ahern (2012) points out, a hypothetical merger announcement in which the acquirer's total gain is \$100 and the target's gain is -\$99 produces the combined synergy of \$1 and the acquirer's relative gain of \$100/\$1=100, or 10,000%.

variables used in Table 2, CBN_Recent and CBN_Old. Column 5 (Column 6) of Table 4 reports the estimation results from the OLS regression of Eq. (10) using the alternative CBN variables as the main explanatory variables and $CombCAR3$ ($AcqGain3$) as the dependent variable. The results in the columns show that only CBN_Recent has explanatory power, consistent with H2 and also with the earlier merger likelihood results reported in Table 2.

Last, we address the concern that our results are driven by cash deals certified by the presence of bank financing, as shown in Bharadwaj and Shivdasani (2003). In so doing, we estimate Eq. (10) with an extra interaction term between CBN and the binary variable for 100% stock deals. If our results documented so far are driven solely by bank-financed cash deals, the coefficient of the interaction term should be negative because deals paid for with 100% stock are not subject to monitoring by the lenders for the merger financing. Column 7 (Column 8) of Table 4 reports the test results using $CombCAR3$ ($AcqGain3$) as the dependent variable. In Column 7, the coefficient on $CBN\_Recent \times 100\%\ stock$ is positive and insignificant, which is inconsistent with the alternative explanation. Additionally, the positive and significant coefficient of the interaction term shown in Column 8 is consistent with Hansen (1987), who shows that an acquirer with a superior bargain position can reduce potential overpayment to the target by making an all-stock offer, thereby forcing the target into internalizing part of the overpayment costs.

The empirical results in this section indicate that low search costs due to shared bank networks bring firms with close complementary assets together, and when the merger is consummated, the shareholders of the merging firms can achieve greater post-merger synergistic value.

4.3. Alternative explanations

We interpret our findings as evidence that lower search costs owing to firm connections through CBNs allow acquirers to achieve better assortative matching. This section presents additional evidence supporting this interpretation by investigating alternative arguments that CBN connections merely capture the firms' information environments or latent quality.

4.3.1. Are CBN connections a byproduct of firms' information environments?

First, we address the alternative explanation that the information environments surrounding firms in the merger market can fully explain both the likelihood of having complementary mergers and CBN connections. That is, high-quality information environments (i.e., low level of information asymmetry) allow firms with complementary assets to consummate mergers more easily and also to have easier access to loan capital, thus forming CBN connections as byproducts. Then, the quality of information environments would explain our empirical results more effectively than CBN connections.

To address this confounding explanation, we estimate the baseline regression models augmented with additional variables that capture the quality of the information environments surrounding the firms. Specifically, we employ the following seven measures commonly found in the literature as proxies for information asymmetry: firm size, asset tangibility, number of years since IPO, abnormal accruals, number of analysts publishing annual earnings per share (EPS) forecasts, idiosyncratic volatility, and bid-ask spreads. We construct these proxies for both acquirers and targets following the variable specifications from Karpoff et al. (2013) and also from Masulis and Simsir (2018).[35] One way of testing the information environment-based explanation is to include all of the 14 control variables in the model estimation. However, as Karpoff et al. (2013) point out, implementing all of the variables at once in a single regression will give rise to severe multicollinearity as well as attenuation issues in the estimated coefficients because these variables are highly correlated with each other. Instead, we follow Karpoff et al. (2013) and Masulis and Simsir (2018) and perform factor analysis to extract from these proxies a set of common factors correlated with the extent of information asymmetry surrounding the merging firms.

Table 5 reports the results from the factor analysis on the seven information proxies for both acquirers and targets in the 1,683 sample merger cases. For each firm type, the columns for the three factors report the factor loadings associated with the seven proxies. The first four proxies (i.e., the number of analysts, firm age, firm size, and tangibility) measure the degree of information *symmetry*, whereas the last three (i.e., idiosyncratic volatility, bid-ask spread, and abnormal accruals) measure the severity of information

[35] All variable definitions are presented in Appendix A.

asymmetry. Therefore, we expect that the first four proxies are negatively correlated with a true measure of information asymmetry and the last three are positively correlated. As in Karpoff et al. (2013), the loadings on the first factor for each firm type reported in Column *Factor 1* exhibit the signs that are exactly the opposite of the predicted signs, thus indicating that the first factors capture the degree of information symmetry for both firm types. On the contrary, the other factors in Columns *Factor 2* and *3* show signs on the loadings that are collectively inconsistent with the predictions. Furthermore, the first factors exhibit substantially large eigenvalues (i.e., 2.4505 for acquirers and 2.3266 for targets) compared to the other factors (i.e., eigenvalues all less than 1, below the level commonly considered relevant), indicating that the most common variations among the proxies are reflected in the first factors. Last, the Kaiser-Meyer-Olkin (KMO) sampling adequacy index values reported in the table indicate that the proxies make a reasonably strong contribution to the common variations both individually and collectively, further validating our use of factor analysis.

Next, we construct the information asymmetry measures for both the acquirers and the targets using the first factors from the factor analysis. We multiply the measures by -1 to convert them to the measures of information asymmetry because the factors capture information symmetry. Then, we augment Eq. (7) with the following four additional control variables, that is, the interaction terms between Q-closeness and information asymmetry for the acquirers and the targets as well as the two stand-alone information asymmetry measures. The idea is that if the CBN connections are just a byproduct of the firm-level information environment, the explanatory power of the main interaction term, $-|AcqQ - TarQ| \times CBN\_Recent$, will be completely subsumed by the additional variables capturing the quality of the firms' information environments.

Columns 1 and 2 in Panel A of Table 6 report the estimation results. The coefficients of $-|AcqQ - TarQ| \times CBN\_Recent$ continue to be statistically and economically significant. The new interaction terms have negative signs, which is consistent with the notion that poor information environments hinder the ability of the firms with complementary assets to consummate mergers. However, the statistical significance of the information variables is weak in the presence of CBN_Recent, with only one estimate in Column 2 being significant at the 10% level. Together, the results are inconsistent with the alternative explanation that CBN connections provide a broader range of channels for reducing search costs than the firms' information environments.[36]

Next, we further test the effect of information asymmetry on CBN using the OLS Eq. (10) augmented with the two information asymmetry measures. Columns 1 and 2 in Panel B of Table 6 report the results using the combined return and the acquirers' relative share of the gain as the dependent variables, respectively. The estimates on the target information asymmetry are positive and significant, and this result is consistent with the acquirers' gain on targets' information asymmetry documented by Officer, Poulsen, and Stegemoller (2009). Still, the estimates on CBN_Recent are economically and statistically highly significant. Taken together, the test results shown in Columns 1 and 2 in both panels of Table 6 reject the alternative explanation that CBN captures merely the quality of firm-level information environments.

4.3.2. Are CBN connections a byproduct of bank and firm quality?

Next, we focus on the possibility that being connected through a CBN is correlated with latent firm characteristics, such as high firm quality, rather than low search costs. The idea is that perhaps only high-quality firms have access to a few large, prestigious banks and also that high-quality firms tend to merge. To address this alternative explanation that bank and firm quality, rather than firm connections through CBNs, explains our results, we adopt an empirical strategy in which we identify two subsets of the initial 1,426 non-CBN mergers with comparable bank quality and firm quality to the CBN deals. By varying the status of connection via a CBN while keeping the bank quality and firm quality comparable, we can mitigate the effect of the confounding factors and more convincingly attribute the merger outcome to the firms connected via the CBN.

For the first comparator set, *Overlapping deals,* deals are selected so as to have comparable bank quality to that in the CBN mergers. We identify 219 non-CBN deals in which all the acquirer and target firms in

[36] Additionally, we perform 14 sensitivity tests on each of the 14 proxies for information asymmetry using the augmented logit model and report the results in Online Appendix D. Consistent with the results in Panel A of Table 6, all of the estimates of -|AcqQ-TarQ| × CBN_Recent remain statistically significant at least at the 5% level.

the deals hold loan facilities from the same banks that lent to the acquirers and the targets in the CBN deals before the merger announcement. To minimize the year effects, we ensure that the loans in this subset are originated in the same years as the loans from the same banks that constitute the CBN mergers. Appendix B illustrates in detail how the overlapping deal group is constructed. For the second set, *Expired CBN deals*, deals are selected to have firm quality comparable to that in the CBN mergers (i.e., firms good enough to be connected through a CBN). We identify 71 non-CBN deals in which the acquirer-target pairs once were once connected via a CBN but the loans that constituted the relationship had expired, and the firms are no longer connected at the time of the merger announcement. To ensure that the reason for the absence of an active CBN is not related to the firms' asset pledgeability, we require that all firms in this group have at least one outstanding loan at the merger announcement.[37]

Appendix C compares the differences in firm and deal characteristics between the CBN merger group and the non-CBN merger groups in the sample. The comparator sets are designed to match the CBN deals on the latent bank and firm quality; therefore, we expect that the deals in the overlapping and the expired CBN groups are significantly more comparable to the CBN deals than the overall non-CBN deals shown in Column 2. Columns 3 and 6 (Columns 4 and 7), which report the characteristics of the overlapping deals (the expired CBN deals) and how the deals compare with the CBN deals, confirm that the comparator sets are more similar to the CBN deals.

Next, we test the alternative explanation using Eq. (7). In so doing, we take an empirical strategy of comparing actual mergers consisting of the CBN deals, the overlapping deals, and the expired CBN deals (henceforth, we refer to the subsample encompassing these three deal-groups as *Comparable quality sample*) to matched hypothetical mergers. In addition to the matching criteria described for the baseline test in Section 4.1., we also require that the non-merger matched firms have loans from the same banks that constitute the Comparable quality sample deals in order to control for the banks and firm quality across all deals (i.e., the merger deals and the matched control deals). Note that the firm pairs in the matched non-

[37] These two subsets, namely overlapping deals and expired CBN deals, are not mutually exclusive: more than two-thirds of the expired CBN deals also appear in the overlapping set.

merger control sample can have CBN connections as well as overlapping and expired CBN relationships that arise naturally during the matching process.

We then estimate Eq. (7) on two matched samples constructed using the Comparable quality sample. If CBN simply signifies the bank and firm quality rather than firm-to-firm connections, estimating the model using these matched samples will deprive CBN of explanatory power because the bank and firm quality in the comparator deals is similar to that in the CBN deals. Columns 3 and 4 in Panel A of Table 6 report the estimation results. Note that the models also include information asymmetry variables. Regardless, the coefficients on $-|AcqQ - TarQ| \times CBN\_Recent$ continue to be statistically and economically significant, and this result is inconsistent with the alternative explanation. Next, we test H3 by estimating the OLS Eq. (10) for merger announcement returns only using the Comparable quality sample. Columns 3 and 4 in Panel B of Table 6 report that the coefficients on CBN_Recent are positive and significant, and this is, again inconsistent with the alternative explanation. Overall, the findings in the section reject the notion that the latent bank and firm quality factors drive the baseline results.

4.4. Post-merger operating performance

Thus far, our analysis focuses on low-cost searches resulting in mergers with superior announcement return for the merging firms' shareholders. We change our focus and test whether mergers stemming from low search costs exhibit real effects beyond positive stock market reactions. The two operating performance measures employed for this test are changes in the return on assets (Δ*ROA[0,+1]yrs* and Δ*ROA[0,+2]yrs*) and changes in asset turnover (Δ*ATover[0,+1]yrs* and Δ*ATover[0,+2]yrs*); all are measures for the performance in the first year or the first two years following the merger completion.

The following data procedure yields the four measures of operating performance. First, for each acquirer and target in a merger deal, we take two alternative matching techniques to construct a matched control group. For nearest-neighbor (propensity-score) matching, each acquirer-target pair of a deal announced in fiscal year y is matched with up to five pairs of non-merger Compustat firms from the same year (i.e., fiscal year y-1) and industry based on a Mahalanobis distance (logit) model by asset size, Q, and one-year past return. Then, to generate performance measures of the control merger group, we first calculate the average one- and two-year post-merger changes in ROA and asset turnover separately for the acquirer control groups and the target control groups. For example, one-year (two-year) post-merger changes in ROA are calculated by subtracting the ROA observed in the first fiscal year-end from the ROA observed in the second (third) fiscal year-end after the merger completion date, as reported in the SDC database. Next, we use the total assets of the actual acquirer and the target observed in the last fiscal year-end (i.e., fiscal year y-1) before the merger announcement date to construct asset weights and compute the weighted averages of the two control groups' average changes in the measures. Last, we generate the matched group-adjusted changes in ROA and asset turnover (i.e., the four operating performance measures) by subtracting the weighted average of the measures of the control groups from the actual merged firms' post-merger changes in the measures.

Table 7 presents the matched group-adjusted post-merger operating performance based on nearest-neighbor matching (Panel A) and propensity score matching (Panel B). Column 1 of both panels shows that the common bank deal group exhibits substantial and persistent post-merger improvements in ROA and asset turnover, with the [0,+2] year period showing greater improvements than the [0,+1] year period in all cases. In contrast, Columns 2 and 3 of both panels report that the two non-CBN deal groups exhibit weak operational improvements, with the changes slowing down substantially in the [0,+2] year period. The group-to-group comparison results reported in Columns 4 and 5 highlight the growing performance gap between the common bank deal group and the other deal groups. Overall, the evidence presented in Table 7 confirms that the mergers resulting from lower search costs exhibit a substantial improvement in long-term post-merger operating efficiency compared to other deal types. These results, coupled with the previous results on announcement returns, provide consistent and strong support for our predictions in H1 and H3 that low search costs improve the quality of mergers.

4.5. Post-merger changes in asset volatility and loan spreads

Thus far, our analysis indicates that bank-facilitated mergers are associated with superior synergistic value for the merging firms' shareholders. However, it is not clear from the results whether such mergers, namely the CBN mergers, are also beneficial to the banks facilitating the search process. Our theory suggests that the bank with existing loans to the merging firms at the time of the merger announcement essentially faces a payoff schedule equivalent to that of holding a short position on a European call option (Jensen and Meckling, 1976). If a merger between its borrowers proves to be a highly risky project, the bank can suffer a value loss in the existing loans even if the merger is a positive net present value (NPV) project for the merging firms' shareholders. Naturally, a rational bank would not facilitate a merger between its borrowers that would lead to such a transfer of its wealth to the merging firms. In this section, we examine this prediction by testing H5, which states that CBN mergers are not associated with increased asset risk.

We construct a measure that captures changes in the asset volatility of the merging firms before and after the mergers. First, we employ the Merton model approach (Merton, 1974) used in Levine and Wu (2020) to numerically generate pre-merger daily market asset return over a one-year period that ends three months before the announcement date for both the acquirer and the target. Next, we generate the pre-merger combined volatility by computing a simple weighted average standard deviation between the standard deviations of the acquirers' and targets' asset returns. For post-merger volatility, we estimate the combined firm volatility by accounting for the diversification effect of the pooled asset returns. Finally, we construct a measure for changes in asset volatility by normalizing the difference between the post- and pre-merger volatility by the pre-merger volatility. The Merton model approach using the pre-merger announcement data mitigates the concern of the zero debt volatility assumption associated with conventional approaches that compare the pre- and post-merger operating cash flow volatilities.[38] However, this approach is based on a strong assumption that the volatility of the combined firms' assets is not affected by synergy between the two firms' assets. To address this concern, we take an alternative approach of generating the consummated post-merger asset volatility using the post-merger data of the merged firm over the one-year period starting one day *after* the deal′s completion date reported in the SDC database. Appendix D provides detailed descriptions on how the variables are generated.

[38] See Levine and Wu (2020) for a full exposition of the benefits and concerns of this approach.

Table 8 reports the estimation results of an OLS regression model in which the changes in asset volatility are regressed on CBN_Recent. To control for cross-industry and year variations in asset volatility, each model includes fixed effects for the acquirer and target industries as well as year fixed effects. Columns 1 and 2 report estimation results based on the asset volatility constructed using the pre-merger announcement data only (i.e., $\Delta\ Asset\ volatility$ 1), whereas Columns 3 and 4 report estimation results based on the asset volatility constructed using both the pre- and post-merger data (i.e., $\Delta\ Asset\ volatility$ 2). The coefficient of CBN_Recent across the model specifications is negative and mostly insignificant, suggesting that CBN mergers are not associated with a greater increase in asset risk compared to other merger types.

The previous results on changes in asset volatility and also on announcement return imply that there is a negative association between merging firms' having CBNs and the post-merger borrowing costs.[39] We directly test this prediction using the loan spread information obtained from DealScan. The first-best approach for the test would be to compare the average pre-merger loan spreads for the acquirer and the target to the loan spreads for the post-merger combined firm. The technical challenges with this approach are that loan spreads are a function of many firm and loan contract characteristics and that there is typically more than one loan facility per firm during pre- and post-merger periods. Instead, we estimate the following OLS model separately for the loans extended to pre-announcement acquirers and targets as well as the loans extended to post-merger combined firms:

$$Loan\ spreads_t = \beta \times CBR + \Gamma_{t-1}B_{t-1} + FE + \varepsilon_t, \tag{12}$$

where *Loan spreads* is $Ln(ALLINDRAWN)$, the log-transformed $ALLINDRAWN$ attained from DealScan, which is the spread over LIBOR plus the transaction fee determined at the time of loan origination. Γ is an array of the standard borrower and loan contract characteristics known in the banking literature to affect loan spreads and FE is a vector that includes the controls for the borrower industry, loan type, and year fixed effects. In constructing the loan samples, we begin with the initial 1,683 completed merger deals and collect information on loans that the merger participants originated before merger announcement dates and

[39] We thank the anonymous referee for calling our attention to this additional prediction.

also on those originated after the merger completion dates. To minimize potential noise from confounding events, we include only loan facilities extended to the sample acquirers or targets during the 365-day period that ends one day prior to the merger announcement date or to merged firms during the 365-day period that begins one day after the merger completion date. For the post-merger loan sample, we include only the records in which the fiscal end date of the corresponding COMPUSTAT observation for each loan record is dated after the merger completion date to correctly account for the borrowers' post-merger characteristics.

The impact of the CBN on the firm's ability to generate cash flows should appear only after the assets of the merging firms are combined; therefore, the empirical prediction is that β in Eq. (12) should be insignificant for the pre-merger loan sample, whereas β should be significantly negative for the post-merger loan sample. Consistent with the predictions, Table 9 reports that the coefficients on CBN_Recent in the first two columns on the pre-merger loans are statistically indistinguishable from zero, while the coefficient in Column 3 on the post-merger loans is negative and statistically significant at the conventional levels.

A potential spurious relationship could exist such that some time-invariant latent firm characteristics is correlated with both CBN_Recent and the firms' choice to secure bank loans during either of the two different time periods. To address this concern, we construct panel data that include both pre- and post-merger loan observations such that, for each deal, an acquirer's loans appear during both the pre- and the post-merger periods. Estimating the following OLS model using the panel data allows us to check for the within-firm changes in loan spreads over the two time periods:

$$Loan\ spreads_t = \gamma CBR \times Post\_merger + \delta CBR + \eta Post\_merger + \Gamma_{t-1} B_{t-1} + FE^{'} + \varepsilon_t. \qquad (13)$$

$Post\_merger$ is a dummy variable that takes the value of 1 if a loan observation is from the one-year post-merger completion period and 0 if the observation is from the one-year pre-merger announcement period. FE' includes the controls for year, loan type, and deal level fixed effects to ensure that acquirer- and deal-specific time-invariant factors are removed. Column 4 of Table 9 reports the panel regression result. Note that the explanatory power of the stand-alone CBN_Recent is completely subsumed by the deal fixed effects owing to its lack of variation within a deal. More importantly, the coefficient of the key explanatory variable, $CBN\_Recent \times Post\_merger$, is negative and statistically significant, with its economic magnitude highly comparable to that of the coefficient of CBN_Recent in Column 3.[40] With a reduction in the prevailing discount rate, we infer that the value of the outstanding loans extended to the firms in CBN deals before merger announcement will increase, thereby propping up the overall value of the loan portfolios of the banks that facilitate these mergers. From these results, we draw the inference that the banks offer assistance in the acquirers' search for complementary mergers by decreasing search costs only when doing so benefits the banks.

5. Conclusions

Rhodes-Kropf and Robinson (2008) have extended the literature concerning the boundaries of a firm formalized by Grossman and Hart (1986) and Hart and Moore (1990) into the assortative matching theory of mergers. Surprisingly, whereas many papers focus on the effect of asset complementarities on merger activities, little attention has been paid to the search and bargaining process that leads complementary firms to synergistic mergers. To the best of our knowledge, this paper is the first cross-sectional study to show theoretically and empirically that a reduction in search frictions increases the likelihood of complementary mergers and post-merger synergistic value.

Does search matter in the redrawing of firm boundaries? Throughout the paper, we attempt to answer this question. Building on Rhodes-Kropf and Robinson's (2008) theory, we show theoretically as well as empirically that lower search costs facilitate mergers with higher asset complementarities and synergy. The synergy gains are not distributed evenly between the acquirer and target; the acquirer, which commands greater bargaining power from being assisted by the common bank, attains a larger share. Next, we evaluate the post-merger long-term operating performance of mergers in CBNs and find that the performance improves over a three-year horizon after the completion of the merger. Finally, we find that the combined firms from CBN mergers exhibit lower post-merger cost of debt, inconsistent with asset substitution. We

[40] Considering that the pre-merger portion of the loan data for Column 4 does not include the loans extended to the targets and that targets tend to have higher asset volatility than acquirers, the economic magnitude (-0.1985) of the coefficient of the interaction term is likely to be on the conservative side. We refer to the summary statistics on acquirers' and targets' asset volatility reported in Panel B of Table 1 in Levine and Wu (2020).

test the validity of alternative explanations motivated by information asymmetry and latent firm quality and find no support for these explanations. In combination, these results provide evidence that lower search costs allow firms with complementary assets to better locate each other and combine through mergers, thus facilitating the more efficient redrawing of firm boundaries.

One interesting research avenue for future studies on the role of search in the context of the property rights theory is to study how a reduction in search frictions may alleviate investment inefficiency associated with holdup problems. Klein, Crawford, and Alchian (1978) show that rational firms tend to underinvest in relationship-specific assets fearing post-investment rent-seeking by their transaction partners. If low search costs allow the firms to easily find other firms outside the relationships that place high value on the relationship-specific assets, the firms, now with more abundant outside options due to higher search efficiency, will be more willing to invest in the particular assets. Future studies in this area will further expand our understanding of the role of search as one of the key determinants of corporate behavior.

Appendix A: Variable definitions (in alphabetical order)

Abnormal accruals is a continuous variable that reflects performance-adjusted abnormal accruals in a firm's financial statements. To construct the variable, we first estimate the modified Jones (1991) model using the Compustat firms during the 1991-2016 period and attain the residuals to generate the firm-level abnormal accruals. Then, we subtract from each firm's abnormal accruals the median abnormal accruals of the performance-matched portfolio. See Karpoff, Lee, and Masulis (2013) for the exact data procedures.

|AcqQ-TarQ| is a continuous variable that captures the absolute difference in the log-transformed market-to-book asset between the acquirer and the target.

AcqBankNetwork-All is a log-transformed count variable that equals the total number of the current borrowers of the acquirer's banks, counted at the merger announcement. Specifically, we require the borrowers' loans to be led by the same lead banks of the acquirer's outstanding loans at the time of the merger announcement.

AcqBankNetwork-TarPeers is similar to *AcqBankNetwork-All* except that we only count the borrowers that are operating in the same sector (i.e., same two-digit SIC code) and are of a similar size (i.e., the difference in market equity being within 10%) as the target firms.

AcqCAR3 (TarCAR3) is acquirers' (targets') three-day [-1, +1] cumulative abnormal returns surrounding the merger announcement date [0], estimated using the Fama-French-Carhart daily four-factor returns available on Kenneth French's website. The estimation window is established as [-250, -7] days relative to the announcement date with a minimum 100 non-missing CRSP stock return observations required.

AcqGain3 is the acquirer's relative value gain over the three-day period surrounding the merger announcement date and it is generated using the following formula:

$$AcqGain3 = \frac{AcqME \times AcqCAR3 - TarME \times TarCAR3}{AcqME + TarME},$$

where *AcqME* and *TarME* are the market equity of the acquirer and the target measured 10 trading days before the announcement date, respectively.

Acq_tar distance is a continuous variable that measures the geodetic distance (in miles) between the headquarter locations of an acquirer and a target in a deal. The firms' headquarter locations are proxied by the five-digit postal code reported in their 10K. If the postal code is not available, we use the firms' postal code provided in Compustat to proxy the location.

Bid-ask spread is a continuous variable constructed by taking the average of the daily bid-ask spread measured at each day's market closure over the 240 trading days that end 10 days before the announcement date.

Cash is the ratio of cash and cash equivalents to the total book assets.

***CBN** (i.e., Common bank network)* is a binary variable that takes the value of 1 if the following two conditions are met and takes the value of 0 otherwise. The two conditions are: (i) two firms have loan facilities originated from bank syndicates headed by the same lead bank at any time prior to merger announcement date; and (ii) both firms' loan facilities from the common bank are not expired at the time of the merger announcement. We define a bank as a lead bank if DealScan assigns lead arranger or agent credits to the bank.

CBN_Recent is a binary variable that takes the value of 1 if the following two conditions are met and takes the value of 0 otherwise. The two conditions are: (i) two firms have loan facilities originated from bank syndicates headed by the same lead bank during the four-year pre-merger announcement period that ends on one day before the merger announcement date; and (ii) both firms' loan facilities from the common bank are not expired at the time of the merger announcement. We define a bank as a lead bank if DealScan assigns lead arranger or agent credits to the bank.

CBN_Old is a binary variable that takes the value of 1 if the following two conditions are met and takes the value of 0 otherwise. The two conditions are: (i) two firms have loan facilities originated from bank syndicates headed by the same lead bank more than four years (i.e., 1,460 days) before the merger announcement date; and (ii) both firms' loan facilities from the common bank are not expired at the time of the merger announcement. We define a bank as a lead bank if DealScan assigns lead arranger or agent credits to the bank.

CombCAR3 is the acquirer-target combined announcement return constructed using the following formula:

$$CombCAR3 = \frac{AcqME \times AcqCAR3 + TarME \times TarCAR3}{AcqME + TarME},$$

where *AcqME* and *Tar.ME* are the market equity of the acquirer and the target measured 10 trading days before the announcement date, respectively. *TarME* is adjusted for the acquirer's toehold.

Common IB is a binary variable that takes the value of 1 if the acquirers' current IB advisors overlap with the targets' past IB advisors hired for M&A and equity issuance deals any time prior to the merger announcement and takes the value of 0 otherwise.

Facility amount is a continuous variable for the total dollar value of a loan facility reported in DealScan.

Firm size is a continuous variable constructed by log-transforming total book assets.

Firm age is a count variable that reflects the number of years a firm appears in the COMPUSTAT universe before the merger announcement date.

Idiosyncratic volatility is a continuous variable constructed by taking the average of the daily idiosyncratic volatility over the 240 trading days that end 10 days before the announcement date. Daily idiosyncratic volatility is constructed by first fitting the Fama-French-Carhart four factor model (Carhart, 1997) on each firm's daily return data during the 240 day period and attaining the residuals for each firm.

Institutional ownership is the ratio of all of a firm's outstanding shares owned by all of the form-13F filing institutional investors to the firm's total shares outstanding, as observed in the 13F filings reported in the last quarter-end prior to the merger announcement.

Leverage is the ratio of short-term debt plus long-term debt to market assets.

Lender count is a count variable for the number of participants in a loan syndicate.

Market assets is book assets minus book equity plus market equity.

Market equity is a continuous variable for a firm's market value of equity and is constructed by multiplying the stock price and the number of common shares outstanding.

Maturity is a continuous variable for the time to maturity (expressed in months) on a loan facility set at the time of the loan origination.

Number of analysts is a count variable that reflects the median number of annual EPS forecasts published each month prior to the actual 10-K report date. Firm-years with a missing value is considered not having analyst coverage. We add 1 to the value before log-transforming it.

Outstanding loan is a count variable reflecting a firm's total number of outstanding loan facilities reported in DealScan on the merger announcement date.

Past return is the buy-and-hold stock return of a firm minus the buy-and-hold return of the value-weighted market portfolio during a 12-month period ending 2 months prior to the merger announcement date.

Q is a firm's market-to-book assets ratio.

R&D is the ratio of research and development expenditures to the total sales.

ROA is the ratio of operating income before depreciation to the total book assets.

Performance pricing is a binary variable that takes the value of 1 if DealScan reports that the loan contract includes a performance pricing clause and takes the value of 0 otherwise.

Rated is a binary variable that takes the value of 1 if a firm has a Standards and Poor's credit rating in a particular year and takes the value of 0 otherwise.

Relative deal size is the ratio of the deal value to the *Market assets* of the acquirer, which is measured 10 days prior to merger announcement.

Same industry is a binary variable that takes the value of 1 if the primary businesses of the acquirer and the target share the same four-digit SIC code and takes the value of 0 otherwise.

Secured is a binary variable that takes the value of 1 if the loan contract has collateral and takes the value of 0 otherwise.

Tangibility is a ratio of a firm's plant, property, and equipment to total book assets.

TarBankNetwork-All is a log-transformed count variable that equals the total number of the current borrowers of the target's banks, counted at the merger announcement. Specifically, we require the borrowers' loans to be led by the same lead banks of the target's outstanding loans at the time of the merger announcement.

TarBankNetwork-AcqPeers is the same count measure as *TarBankNetwork-All* except that we only count the borrowers that are operating in the same sector (i.e., same two-digit SIC code) and are of a similar size (i.e., the difference in market equity being within 10%) as the acquirer firms.

TarIndustryPeers is a log-transformed count variable that equals the total number of firms that operate in the same sector (i.e., same two-digit SIC code) and are of a similar size (i.e., the difference in market equity being within 10%) as the target firm in the deal in the Compustat universe in the year when merger announcement occurs.

Tender offer is a binary variable that takes the value of 1 if the SDC indicates that the deal is a tender offer and 0 otherwise.

Toehold is a binary variable that takes the value of 1 if the SDC indicates that the acquirer holds shares of the target firm prior to the merger announcement and takes the value of 0 otherwise.

100% Cash deal is a binary variable that takes the value of 1 if the merger consideration is composed entirely of cash and takes the value of 0 otherwise.

100% Stock deal is a binary variable that takes the value of 1 if the merger consideration is composed entirely of the acquirer's stock and takes the value of 0 otherwise.

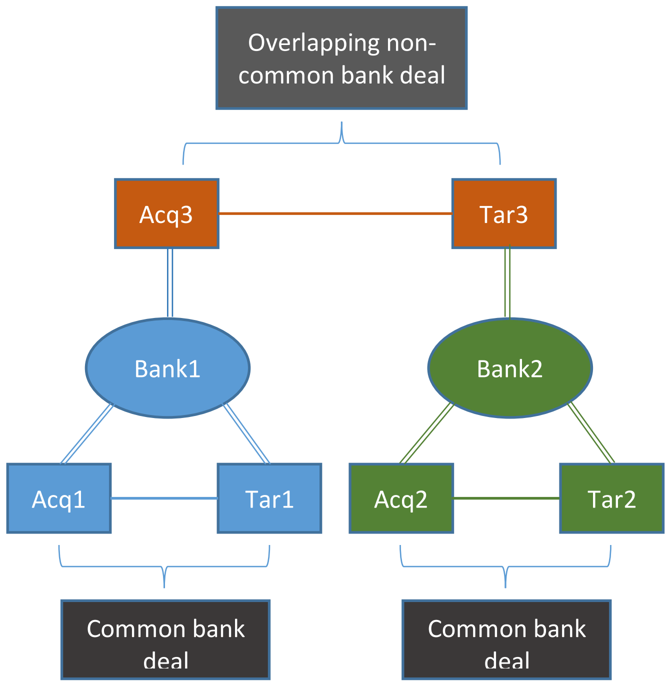
Z-Score is computed following Altman (1968) as:

$$Z\text{-}score = 1.2 \times WC/TA + 1.4 \times RE/TA + 3.3 \times EBIT/TA + 0.6 \times ME/TL + SALE/TA$$

where *WC* is working capital, *RE* is retained earnings, *EBIT* is earnings before interest and taxes, *ME* is market value of equity, *TL* is book value of total liabilities, *SALE* is total sales, and *TA* is total book value of assets.

Appendix B: Definition of overlapping non-CBN deals

We construct a subset of the sample deals in which all of acquirer firms and target firms in the deals take loan facilities from the same banks that lend to the acquirers and the targets in the CBN deals before merger announcement. To minimize the year effects, we ensure that the loans in this control sample are originated in the same years as the loans from the same banks that constitute the common bank mergers. We refer to this subset of the deal sample that consists of the overlapping non-CBN deals as *Overlapping deals*.



Appendix C: Comparison between CBN and non-CBN deal groups

This table reports summary statistics for the sample of 1,683 completed mergers during the 1992-2016 sample period. Repurchases, recapitalizations, minority share purchases, exchange offers, spin-offs and privatizations are all excluded from the sample. Deals with size less than $1 million, deals with the ratio of deal size to the market value of acquiring firms less than 1%, and deals with firms from the financial and utility industries are excluded from the sample. All sample acquirers and targets are US public firms listed on the NYSE, NASDAQ, or AMEX. See Appendix A and Online Appendix C respectively for detailed variable descriptions and for the data filtering process. Column 1 reports statistics of the common bank network (CBN) deals, and column 2 reports statistics of all of the non-CBN deals in the sample. Column 5 reports the differences-in-means test results of the two groups. We identify two subsets consisting of the non-CBN sample deals comparable to the CBN deals: *Overlapping deals* and *Expired CBN deals*. *Overlapping deals* comprise of the non-CBN deals in which all of acquirer firms and target firms take loan facilities from the same banks that lend to the acquirers and the targets in the CBN deals before merger announcement. To minimize the year effects, we ensure that the loans in this control sample are originated in the same years as the loans from the same banks that constitute the common bank mergers. *Expired CBN deals* comprise of the non-CBN deals in which the acquirer-target pairs were once connected through a CBN but at least one of the loans that constituted the relationship has been expired at the time of the merger announcement. To minimize the concern that the loss of bank relationship is correlated with the firms' ability to raise loan capital, we require both acquirers and targets in the expired CBN group to have outstanding bank loans at the time of the merger announcement. Note that the two subsets, overlapping deals and expired CBN deals, are not mutually exclusive and more than a two-thirds of the expired CBN deals also appear in the overlapping sets. Columns 3 and 6 (Columns 4 and 7) report the firm and deal characteristics of the overlapping deals (expired CBN deals) and the differences-in-means test results with the CBN deals, respectively. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	(1)		(2)		(3)		(4)		(5)	(6)	(7)
	CBN deals		Non-CBN deals (All)		Non-CBN deals (Overlapping)		Non-CBN deals (Expired CBN)		Mean diff.	Mean diff.	Mean diff.
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	(1)-(2)	(1)-(3)	(1)-(4)
Firm characteristics											
Acq outstanding loan	5.642	4.674	2.656	3.725	4.826	3.792	4.761	8.714	2.986***	0.816**	0.881
Ln(Acq market equity)	15.628	1.614	14.246	2.002	15.135	1.603	15.558	1.806	1.382***	0.493***	0.070
Acq Q	1.872	1.081	2.734	2.375	2.061	1.315	1.711	0.615	-0.862***	-0.189*	0.160
Acq past return	0.110	0.388	0.134	0.564	0.131	0.405	0.081	0.308	-0.024	-0.021	0.029
Acq ROA	0.186	0.084	0.161	0.154	0.193	0.085	0.192	0.083	0.026**	-0.007	-0.006
Acq leverage	0.206	0.138	0.117	0.123	0.181	0.124	0.178	0.139	0.088***	0.024**	0.028
Acq Z-score	3.186	2.506	6.088	7.439	3.777	3.440	3.625	2.052	-2.823***	-0.581**	-0.439
Acq R&D	0.032	0.048	0.083	0.098	0.025	0.032	0.037	0.039	-0.051***	0.007	-0.005
Acq firm age	31.786	19.018	19.015	16.414	26.516	17.859	32.324	18.532	12.771***	5.270***	-0.538
Acq institution holding	0.699	0.202	0.588	0.255	0.677	0.202	0.731	0.182	0.111***	0.023	-0.032
Tar outstanding loan	4.444	3.337	1.055	1.861	3.228	2.565	2.732	2.171	3.388***	1.215***	1.711***
Ln(Tar market equity)	14.090	1.497	12.091	1.700	13.270	1.424	13.721	1.480	1.999***	0.820***	0.369*
Tar Q	1.674	0.779	2.218	1.840	1.783	0.919	1.731	0.614	-0.544***	-0.109	-0.057
Tar past return	0.060	0.457	-0.018	0.606	0.061	0.489	0.094	0.498	0.078*	-0.001	-0.034
Tar ROA	0.189	0.088	0.096	0.214	0.185	0.098	0.207	0.109	0.092***	0.004	-0.019
Tar leverage	0.229	0.156	0.125	0.151	0.214	0.160	0.182	0.163	0.104***	0.015	0.047**
Tar Z-score	3.037	2.203	5.368	8.159	3.744	4.068	3.571	2.146	-2.358***	-0.729**	-0.535*
Tar R&D	0.040	0.067	0.128	0.145	0.034	0.049	0.052	0.062	-0.088***	0.006	-0.012

Tar firm age	22.981	16.582	13.298	10.770	18.356	14.210	26.169	15.449	9.683***	4.624***	-3.188
Tar institution holding	0.709	0.229	0.426	0.282	0.596	0.251	0.706	0.234	0.283***	0.114***	0.003
Deal characteristics											
Same industry	0.319	0.467	0.255	0.436	0.233	0.424	0.211	0.411	0.064**	0.086**	0.108*
Ln(Acq_tar distance)	5.681	1.933	5.861	2.043	5.950	1.876	5.816	1.944	-0.180	-0.269	-0.136
100% stock deal	0.202	0.403	0.357	0.479	0.210	0.408	0.099	0.300	-0.155***	-0.008	0.104**
100% cash deal	0.230	0.421	0.327	0.469	0.269	0.445	0.423	0.497	-0.098***	-0.040	-0.193***
Tender offer	0.160	0.367	0.238	0.426	0.242	0.429	0.211	0.411	-0.079***	-0.082**	-0.052
Toehold	0.023	0.151	0.029	0.169	0.018	0.134	0.014	0.119	-0.006	0.005	0.009
Relative deal size	0.651	0.768	0.397	0.623	0.513	0.731	0.489	0.669	0.254***	0.137**	0.161
N	257		1,426		219		71				

Appendix D: Constructing pre- and post-merger asset volatility

To construct the asset volatility of each of the acquirer and the target, we follow the steps in Bharath and Shumway (2008) and Lavine and Wu (2018) to numerically solve the following two equations based on the bond pricing model in Merton (1974).

$$\mathrm{ME} = \mathrm{MA} \cdot \mathrm{N}(d_1) - \exp\left(-r_f T\right) F N(d_2) \tag{D.1}$$

$$\sigma_{MA} = [ME/(MA \cdot N(d_1))] \cdot \sigma_{ME} \tag{D.2}$$

where

$$d_1 = \frac{\ln(MA/F) + \left(r_f + 0.5\sigma_{MA}^2\right)T}{\sigma_{MA}\sqrt{T}}$$

and $$d_2 = d_1 - \sigma_{MA}\sqrt{T}$$

r_f is the one-year treasury constant maturity rate, T is 1, F is current liabilities plus one-half of long-term debt, ME is the market value of common equity, and σ_{ME} is the annualized standard deviation of daily stock returns. Through iterations between (1) and (2), I derive the market value (MA) and the volatility (σ_{MA}) of total assets.[41] Using the model, we take two alternative approaches to generate two measures of post-merger asset volatilities. The first approach requires only the pre-deal announcement acquirer and target data to estimate the consummated post-merger asset volatility. The post-merger asset volatility generated using pre-announcement data is shown below:

$$E\left[\sigma_{Acq+Tar}(postmerger)\right] = \sqrt{w_{Acq}^2\sigma_{Acq}^2 + w_{Tar}^2\sigma_{Tar}^2 + 2w_{Acq}w_{Tar}\sigma_{Acq}\sigma_{Tar}\rho} \tag{D.3}$$

where σ_{Acq} (σ_{Tar}) is estimated acquirer (target) asset volatility and $w_{Acq} = \frac{MA_{Acq}}{MA_{Acq}+MA_{Tar}}$ $\left(w_{Tar} = \frac{MA_{Tar}}{MA_{Acq}+MA_{Tar}}\right)$ is the weights for the acquirer's (target's) volatility. The weights are computed using the estimated market value of assets three months before the announcement date. ρ is the correlation of estimated

[41] The SAS code used for the variable construction will be available upon request.

daily asset returns between the acquirer and the target over the one-year period ending three months before the merger announcement date.

The alternative approach of generating consummated post-merger asset volatility involves estimating asset volatility through equations (1) and (2) using the post-merger data of the merged firm over the one-year period starting one day *after* the deal completion date reported in the SDC database.

Following Lavine and Wu (2018) who argue that cash introduces noise to the asset volatility measure, we construct a cash-adjusted measure of asset volatility as below:

$$\dot{\sigma}_i = \left(\frac{MV}{MV-C}\right)\sigma_i \tag{D.4}$$

where C is cash plus short-term investments.

Finally, the expected changes in asset volatility from pre- to post-merger periods is generated as below:

$E[\Delta\sigma_{Acq+Tar}]$ = $(E\left[\dot{\sigma}_{Acq+Tar}(postmerger)\right] - \dot{\sigma}_{Acq+Tar}(premerger))/\dot{\sigma}_{Acq+Tar}(premerger)$ where

$$\dot{\sigma}_{Acq+Tar}(premerger) = w_{Acq} \cdot \dot{\sigma}_{Acq} + w_{Tar} \cdot \dot{\sigma}_{Tar} \tag{D.5}$$

We refer to $E[\Delta\sigma_{Acq+Tar}]$ constructed using the first approach as *Δ Asset volatility 1* and $E[\Delta\sigma_{Acq+Tar}]$ constructed using the second approach as *Δ Asset volatility 2*.

Appendix E: Proofs of propositions

Proof of Lemma 1: Following the standard result in random network literature, we know that, without the help of a bank, the probability of having n number of acquirer-target connections per period when the number of target candidate N is large, is $\lim_{N\to\infty} \frac{N!}{n!(N-n)!} p^n(1-p)^{N-n} = \frac{e^{-1/\kappa}}{\kappa^n n!}$, where $\kappa = \frac{1}{Np}$.[42] Hence, the matching between acquirer and target follows a Poisson process with average arrival time $\frac{1}{\kappa}$. Meanwhile, given the bank's network size M and probability of connection p', banks will feed the acquirer another Poisson sequence of target candidates with average arrival time $\frac{1}{Mp'}$. The Poisson process gives us $f(n;\hat{\kappa})$ for the acquirer with bank-facilitated search. □

An acquirer negotiating with one target candidate can still choose to walk away and start negotiating with another candidate. Such an outside option has a value $V(\theta_A)$ which affects the equilibrium bargaining outcome reciprocally. We show the bargaining outcome given $V(\theta_A)$.

Lemma 2: When the acquirer with type θ_A and outside value $V(\theta_A)$ negotiating with a target candidate with type θ_B, the equilibrium bargaining out is $s(\theta_A, \theta_B, V(\theta_A)) = \frac{1}{2} + \frac{V(\theta_A)}{2\overline{\mu}\kappa(1-|\theta_A-\theta_B|)}$.

The proof of Lemma 2 is in the Online Appendix A. We are now ready to prove Proposition 1.

Proof of Proposition 1: First, the acquirer's outside value without the bank's help is

$$V(\theta_A) = \int_0^1 \int_0^{+\infty} e^{-r\tau} \max(\mu(\theta_A, \theta_B) s(\theta_A, \theta_B, V(\theta_A)), V(\theta_A))\, g(\tau) d\tau f(\theta_B) d\theta_B \tag{E.1}$$

in which $g(\tau) = \frac{1}{\kappa} e^{-\frac{\tau}{\kappa}}$ is the pdf of next candidate arrival time from the Poisson distribution derived in Lemma 1, and $f_{\mathrm{B}}(\theta_B) = 1$.[43] Solve the equation gives us the outside value of acquirer as

$$V(\theta_A) = \overline{\mu} \sum_{n=1}^{+\infty} c_n \frac{\kappa\overline{\mu}(2\kappa-1)^{2n-2}}{[4r\kappa^2\overline{\mu}-2(1-2\kappa)]^{2n-1}}, where\ c_n = (-1)^{n-1}\binom{\frac{1}{2}}{n} \tag{E.2}$$

Since the acquirer can only merge with one target, she has the incentive to screen the candidates: she only enters bargaining with candidates that can bring in high enough synergy, and pass the rest. The

[42] Notice the Stirling's approximation $\lim_{N\to\infty} N! = \sqrt{2\pi N}\left(\frac{N}{e}\right)^N$.

[43] Maximizing the outside value V leads to maximizing the acquirer's shareholder value, which is strictly increasing with the outside value V.

threshold level is therefore $\mu(\theta_A, \theta_B^*(\theta_A))s(\theta_A, \theta_B^*(\theta_A), V(\theta_A)) = \frac{\overline{\mu}(1-|\theta_A-\theta_B^*(\theta_A)|)}{2} + \frac{V(\theta_A)}{2\kappa} = V(\theta_A)$, which gives us $|\theta_A - \theta_B^*(\theta_A)| = 1 - \frac{(2\kappa-1)V(\theta_A)}{\kappa\overline{\mu}} = 1 - \overline{\mu}\sum_{n=1}^{+\infty} c_n \left[\frac{2\kappa-1}{4r\kappa^2\overline{\mu}-2(1-2\kappa)}\right]^{2n-1}$. Since the right-hand side does not depend on $\theta_A \in \{0,1\}$, so does $|\theta_A - \theta_B^*(\theta_A)|$. Hence,

$$\theta_B^*(0) = \theta_B^* = 1 - \overline{\mu}\sum_{n=1}^{+\infty} c_n \left[\frac{2\kappa-1}{4r\kappa^2\overline{\mu}-2(1-2\kappa)}\right]^{2n-1}, and\ \theta_B^*(1) = 1 - \theta_B^*. \tag{E.3}$$

Together with Lemma 2, we obtain the equilibrium bargaining outcome

$$s(\theta_A, \theta_B) = \frac{1}{2} + \frac{1}{2(1-|\theta_A-\theta_B|)}\sum_{n=1}^{+\infty} c_n \frac{\overline{\mu}(2\kappa-1)^{2n-2}}{[4r\kappa^2\overline{\mu}-2(1-2\kappa)]^{2n-1}} \tag{E.4}$$

Similarly, we can solve the outside value of acquirer with bank facilitated searching given $\hat{\kappa} = \frac{1}{Np+Mp'}$, and obtain the threshold $\hat{\theta}_B^*(\theta_A)$ and $\hat{s}(\theta_A, \theta_B)$ accordingly.

$$\hat{\theta}_B^*(0) = \hat{\theta}_B^* = 1 - \overline{\mu}\sum_{n=1}^{+\infty} c_n \left[\frac{2\hat{\kappa}-1}{4r\hat{\kappa}^2\overline{\mu}-2(1-2\hat{\kappa})}\right]^{2n-1}, and\ \hat{\theta}_B^*(1) = 1 - \hat{\theta}_B^* \tag{E.5}$$

$$\hat{s}(\theta_A, \theta_B) = \frac{1}{2} + \frac{1}{2(1-|\theta_A-\theta_B|)}\sum_{n=1}^{+\infty} c_n \frac{\overline{\mu}(2\hat{\kappa}-1)^{2n-2}}{[4r\hat{\kappa}^2\overline{\mu}-2(1-2\hat{\kappa})]^{2n-1}}. \tag{E.6}$$

Now let's consider $\hat{\Pi}(\hat{\theta}_B^*(\theta_A), \sigma')$, the bank's portfolio value when it chooses to facilitate the search, and $\Pi(\theta_B^*(\theta_A), \sigma')$, the portfolio value otherwise. Notice the difference between Π and $\hat{\Pi}$ is exactly the probability weighted average difference of the loan value between an acquirer-target pair, where acquirer's type is θ_A and the target's type $\theta_B \in \Theta_B(\theta_A) = \{\theta_B: |\theta_A - \hat{\theta}_B^*(\theta_A)| \leq |\theta_A - \theta_B| \leq |\theta_A - \theta_B^*(\theta_A)|\}$.[44] Each pair of acquirer and target in the region would only merge under bank facilitated search.

We then quantify the difference of the loan values of the acquirer with type θ_A and target candidate θ_B. Solve the PDEs that govern the loan values, we obtain $\hat{\Pi}(\hat{\theta}_B^*, \sigma') - \Pi(\theta_B^*, \sigma')$ to be

[44] Notice the bank's portfolio value is the sum of all possible acquirer-target loan value weighted by the joint probability density of θ_A and θ_B. Moreover, although the search costs κ and $\hat{\kappa}$ affect the equilibrium threshold $\theta_B^*(\theta_A)$ and $\hat{\theta}_B^*(\theta_A)$ as well as the equilibrium bargaining outcome, they do not affect the post-merger bank loan value and firm value between an acquirer-target pair given θ_A and θ_B. Therefore, whether a bank helps the searching effort of an acquirer with type θ_A does not affect the merger outcome if the acquirer meets with target candidates with type θ_B such that $|\theta_A - \theta_B| > |\theta_A - \theta_B^*(\theta_A)|$, or $|\theta_A - \theta_B| < |\theta_A - \hat{\theta}_B^*(\theta_A)|$: the acquirer would not merge with the former targets and would merge with latter regardless of the bank's participation.

$$\sum_{\theta_A} \pi(\theta_A) \left\{ \int_{\Theta_B(\theta_A)} \mu(\theta_A, \theta_B) \Phi(-\delta') - \frac{\sqrt{T}}{\sqrt{2\pi}} \sigma' e^{-rT - \frac{\delta'^2}{2}} + \sum_{i \in \{A,B\}} \left[D_0^i - V_0^i\right] \left[\Phi(\delta') - \Phi(\delta^i)\right] + \right.$$

$$\left. \frac{\sqrt{T}}{\sqrt{2\pi}} \sigma e^{-rT - \frac{\delta^{i2}}{2}} d\theta_B \right\}, \quad \text{(E.7)}$$

where $\delta^A = \frac{e^{rT}(V_0^A - D_0^A)}{\sigma\sqrt{T}}$, $\delta^B = \frac{e^{rT}(V_0^B - D_0^B)}{\sigma\sqrt{T}}$, and $\delta' = \frac{e^{rT}(V_0^A + V_0^B - D_0^A - D_0^B + \mu(\theta_A, \theta_B))}{\sigma'\sqrt{T}}$.[45]

Recall the symmetry for $\theta_B^* = \theta_B^*(0) = 1 - \theta_B^*(1)$ and $\hat{\theta}_B^*$, it is easy to see that, with $\delta' = \frac{e^{rT}(V_0^A + V_0^B + \overline{\mu}(1-\theta_B))}{\sigma'\sqrt{T}}$ the value difference $\widehat{\Pi}(\hat{\theta}_B^*, \sigma') - \Pi(\theta_B^*, \sigma')$, which equals to

$$\int_{\hat{\theta}_B^*}^{\theta_B^*} \overline{\mu}(1-\theta_B)\Phi(-\delta') - \frac{\sqrt{T}}{\sqrt{2\pi}} \sigma' e^{-rT - \frac{\delta'^2}{2}} + \sum_{i \in \{A,B\}} \left[D_0^i - V_0^i\right] \left[\Phi(\delta') - \Phi(\delta^i)\right] + \frac{\sqrt{T}}{\sqrt{2\pi}} \sigma e^{-rT - \frac{\delta^{i2}}{2}} d\theta_B \quad \text{(E.8)}$$

is continuous and *monotonically* decreasing in σ'. Besides, the bank should encourage the merge if $\sigma' = 0$ and should not if $\sigma' = +\infty$. Therefore, there exists a unique threshold $\hat{\sigma}^*$. □

Proof of Proposition 2: First, we have $\frac{d}{d\kappa} \frac{2\kappa - 1}{4r\kappa^2\overline{\mu} - 2(1-2\kappa)} < 0$. Together with $\kappa > \hat{\kappa}$, we obtain

$$\hat{\theta}_B^* - \theta_B^* = -\sum_{n=1}^{+\infty} c_n \int_\kappa^{\hat{\kappa}} \frac{d}{dx} \left[\frac{2x-1}{4rx^2\overline{\mu} - 2(1-2x)}\right]^{2n-1} dx < 0 \quad \text{(E.9)}$$

which shows the common bank merger leads to a higher asset-complementarity. Further, since $\hat{\kappa} = \frac{1}{Np + Mp'}$, a higher M or p' leads to a lower $\hat{\kappa}$ as well as a higher asset-complementarity. □

Proof of Proposition 3: First, from Lemma 2, we have $s(\theta_A, \theta_B) = \frac{1}{2} + \frac{V(\theta_A)}{2\overline{\mu}\kappa(1 - |\theta_A - \theta_B|)}$. Next, from Proposition 1 and 2 we know that acquirer's outside option $V(\theta_A)$ is decreasing in search cost κ. To see this, notice that $c_n = (-1)^{n-1}\binom{\frac{1}{2}}{n}$ is positive for all n. In addition, after some tedious derivation, we can show that $\frac{d}{d\kappa} \frac{\overline{\mu}(2\kappa-1)^{2n-2}}{[4r\kappa^2\overline{\mu} - 2(1-2\kappa)]^{2n-1}} < 0$ for all n. Hence, the numerator of the second fraction decreases with κ and the denominator increases with κ: so $s(\theta_A, \theta_B)$ decreases with κ, which gives us $\hat{s}(\theta_A, \theta_B) > s(\theta_A, \theta_B)$. □

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45 Please refer to Online Appendix A for the technical details, formations and solution of the loan value PDEs.

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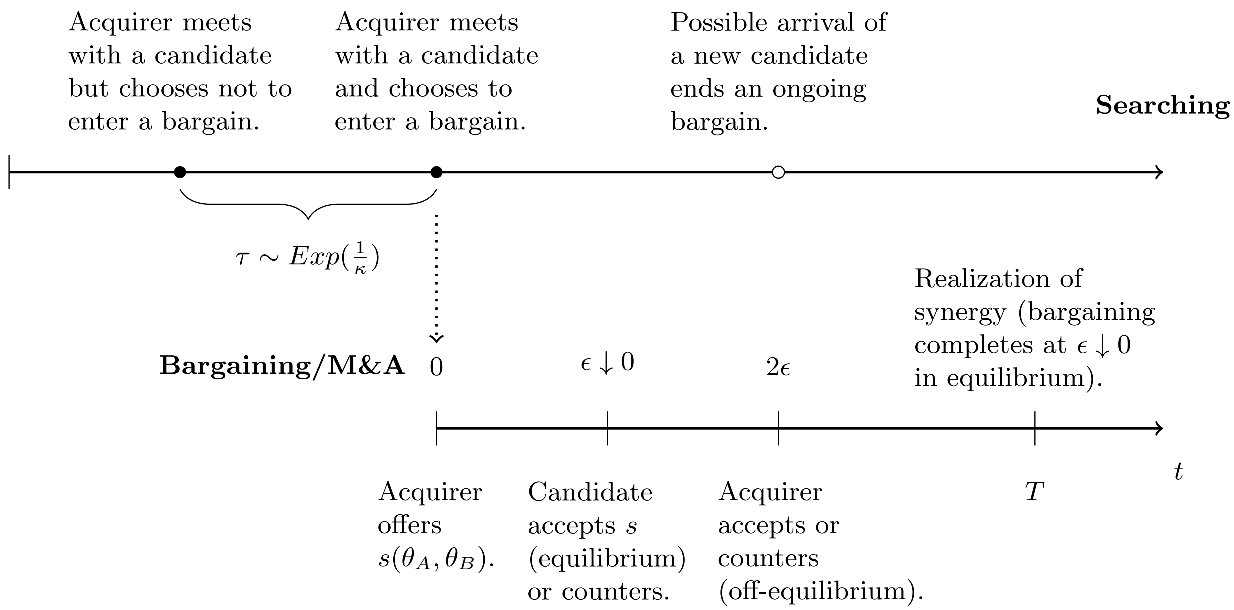
Figure 1: Model timeline

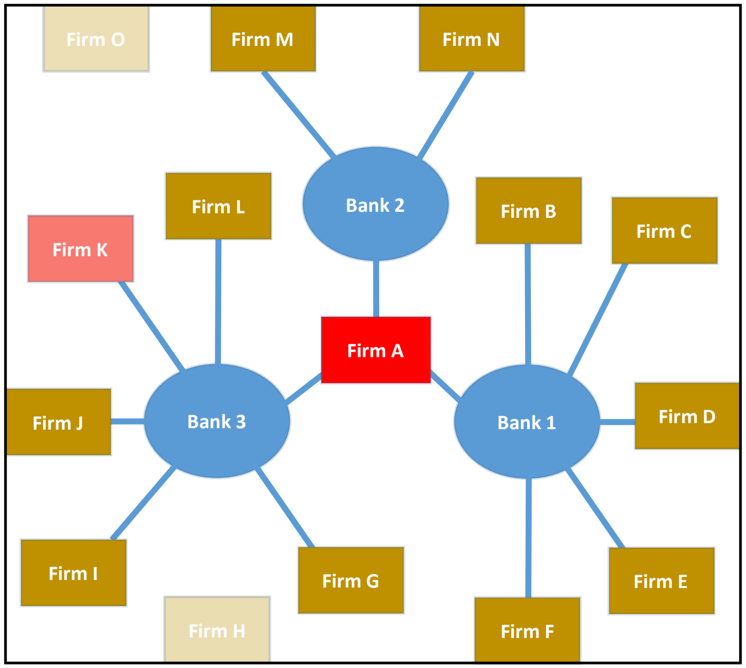


This figure demonstrates the timeline of the model. In the searching stage, an acquirer meets with a candidate with inter-arrival time τ, which is affected by the search cost κ (Lemma 1 suggests the distribution $\tau \sim Exp(1/\kappa)$). Once the acquirer meets with a candidate, she can choose to enter the bargaining stage with the candidate, or pass him and wait for the next one. The bargaining process contains multiple rounds of exchange of alternating offers between the acquirer and the candidate. In round 1, the acquirer extends an initial offer $s(\theta_A, \theta_B)$ at the beginning of the bargain. The candidate takes time $\epsilon \downarrow 0$ to ponder the offer, and he may accept the round 1 offer or counter it with round 2 offer s_t. Similarly, the acquirer can accept the round 2 offer from the candidate or returns with round 3 offer. The acquirer abandons the bargaining when a new candidate arrives. The synergy takes T period of time to realize, whereas in equilibrium the candidate accepts the acquirer's equilibrium offer $s(\theta_A, \theta_B)$ at $t = \epsilon \downarrow 0$ without counteroffering.

Figure 2: Acquirer's bank network

The panels in this figure illustrate two otherwise identical firms, Firm A, connected to bank lending networks of different size. For simplicity, we assume that the entire lending networks in either panels consist solely of likely target candidates. In Panel A, Firm A is connected to a lending network comprising 12 other borrowers, which includes Firm K, the firm that shares the highest level of asset complementarity with Firm A. If the potential merger between the two firms is not expected to induce asset substitution for Bank 3, the bank, which is the common bank between the two firms, has incentives to assist Firm A in discovering Firm K at low search costs. In Panel B, Firm A is connected to a network comprising only 6 other borrowers, which does not include Firm K. Due to high search costs associated with discovering Firm K, Firm A could either settle with a firm in the network or any firm outside the network.

Panel A: Large lending network



Panel B: Small lending network

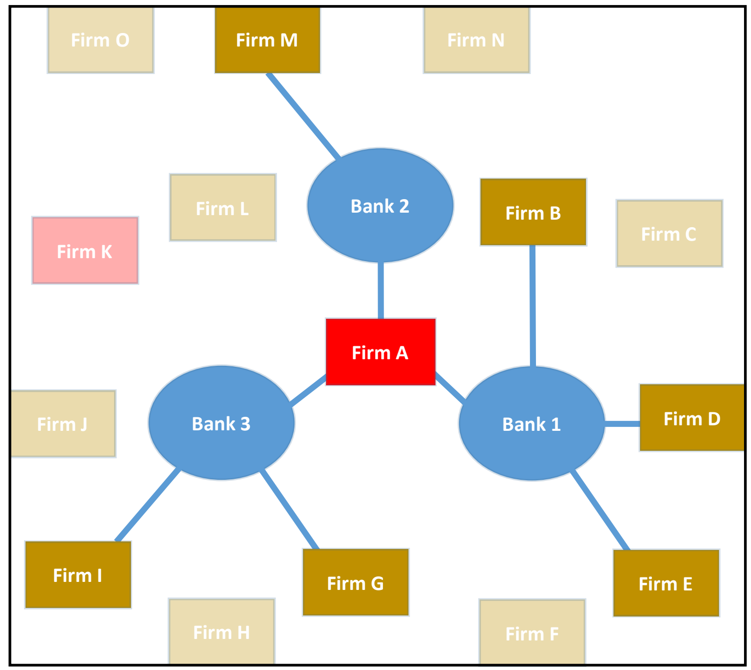


Table 1: Summary statistics

This table reports summary statistics for the sample of 1,683 completed mergers during the 1992-2016 sample period. Repurchases, recapitalizations, minority share purchases, exchange offers, spin-offs and privatizations are all excluded from the sample. Deals with deal size less than $1 million, deals with the ratio of deal size to the market value of acquiring firms less than 1% are excluded, and deals with firms from the financial and utility industries are excluded from the sample. All sample acquirers and targets are US public firms listed on the NYSE, NASDAQ, or AMEX. See Appendix A and Online Appendix C respectively for detailed variable descriptions and for the data filtering process. Panel A reports summary statistics of the firm and deal characteristics for the full sample. We classify a sample merger as a common bank network (CBN) deal if the following two conditions are met: (1) an acquirer and a target from a deal had loan facilities originated from bank syndicates with a common lead bank at any time before the merger announcement date; (2) both firms' loan facilities from the common bank do not expire before the merger announcement date. We define a bank as a lead bank of a loan syndicate if DealScan assigns lead arranger or agent credits to the bank. Panel B reports the annual distributions for all sample mergers, CBN deals (CBN), and a subset of CBN deals in which the merging firms' common bank relationships are formed within four years prior to merger announcement (CBN_Recent).

Panel A: Firm and deal characteristics

	Mean	S.D.	1st Quartile	Median	3rd Quartile
Firm characteristics					
Acq outstanding loan	3.112	4.030	0.000	2.000	5.000
Ln(Acq market equity)	14.457	2.011	13.046	14.446	15.831
Acq Q	2.602	2.248	1.371	1.881	2.839
Acq past return	0.130	0.541	-0.171	0.030	0.312
Acq ROA	0.165	0.146	0.119	0.174	0.241
Acq leverage	0.131	0.129	0.019	0.096	0.207
Acq Z-score	5.801	6.657	2.536	4.031	6.516
Acq R&D	0.076	0.095	0.013	0.050	0.102
Acq firm age	20.966	17.447	7.000	15.000	34.000
Acq institution holding	0.605	0.251	0.455	0.645	0.791
Tar outstanding loan	1.573	2.473	0.000	1.000	2.000
Ln(Tar market equity)	12.396	1.819	11.052	12.344	13.752
Tar Q	2.135	1.731	1.170	1.561	2.409
Tar past return	-0.006	0.587	-0.381	-0.084	0.204
Tar ROA	0.110	0.202	0.069	0.152	0.213
Tar leverage	0.141	0.156	0.003	0.083	0.243
Tar Z-score	5.232	7.264	2.010	3.609	6.073
Tar R&D	0.118	0.141	0.016	0.081	0.159
Tar firm age	14.777	12.339	7.000	9.000	19.000
Tar institution holding	0.469	0.293	0.214	0.468	0.711
Deal characteristics					
Same industry	0.449	0.497	0.000	0.000	1.000
Ln(Acq_tar distance)	5.833	2.027	5.232	6.533	7.300
100% stock deal	0.333	0.472	0.000	0.000	1.000
100% cash deal	0.313	0.464	0.000	0.000	1.000
Tender offer	0.226	0.419	0.000	0.000	0.000
Toehold	0.029	0.167	0.000	0.000	0.000
Relative size	0.436	0.653	0.077	0.224	0.576
N	1,683				

Panel B: Annual distribution of the CBN deals

Year	All ample mergers	CBN		CBN_Recent	
	Count	Count	pct.	Count	pct.
1992	22	0	0.0%	0	0.0%
1993	25	0	0.0%	0	0.0%
1994	64	2	3.1%	2	3.1%
1995	84	5	6.0%	4	4.8%
1996	102	4	3.9%	3	2.9%
1997	128	11	8.6%	8	6.3%
1998	145	4	2.8%	3	2.1%
1999	128	16	12.5%	16	12.5%
2000	129	21	16.3%	17	13.2%
2001	97	14	14.4%	10	10.3%
2002	55	9	16.4%	4	7.3%
2003	62	4	6.5%	4	6.5%
2004	61	7	11.5%	6	9.8%
2005	73	19	26.0%	15	20.5%
2006	60	16	26.7%	16	26.7%
2007	76	17	22.4%	16	21.1%
2008	44	9	20.5%	8	18.2%
2009	50	18	36.0%	15	30.0%
2010	46	9	19.6%	8	17.4%
2011	29	10	34.5%	6	20.7%
2012	34	9	26.5%	9	26.5%
2013	35	12	34.3%	11	31.4%
2014	49	18	36.7%	17	34.7%
2015	49	16	32.7%	16	32.7%
2016	36	7	19.4%	5	13.9%
Total	1,683	257		219	

Table 2: Search efficiency and the likelihood of complementary merger

This table reports estimation results for a logit model. The dependent variable is a binary variable that takes the value of 1 for the actual sample merger deals and 0 for non-merger control deals constructed by matching each acquirer and target in an actual deal with non-merger firms. First, we construct control samples of hypothetical merger deals for the 1,683 actual merger deals in our baseline data set using the following two matching techniques: nearest-neighbor matching, (matching technique 1), and propensity score matching (matching technique 2). For matching technique 1 (2), each acquirer-target pair of an actual deal announced in year y is matched with up to five pairs of non-merger Compustat firms from year y-1 and the same industry using a Mahalanobis distance model (a logit model) by asset size, one-year past return, and the number of outstanding bank loan facilities. Industries are matched by the most granular SIC grouping possible that gives five control firms. *CBN* is the main explanatory variable that takes the value of 1 for an acquirer-target pair being connected through a common bank and 0 otherwise. *CBN_Recent* (*CBN_Old*) is a binary variable that takes the value of 1 if the merging firms' common bank relationships are formed within four years (before four years) prior to merger announcement. Columns 1 and 4 report the results with the absolute difference in the log-transformed market-to-book asset between the acquirer and the target multiplied by -1 capturing the closeness of the acquirer-target Q distance, -|*AcqQ-TarQ*|, as the key explanatory variable. Columns 2 and 5 (Columns 3 and 6) report the estimation results of the baseline models, which include the stand-alone and interaction terms between -|*AcqQ-TarQ*| and *CBN* (*CBN_Recent* as well as *CBN_Old*). All models include year fixed effects. See Appendix A for the detailed variable definitions. Student t-statistics from standard errors clustered by merger deal group is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Matching methods:	Matching 1	Matching 1	Matching 1	Matching 2	Matching 2	Matching 2
-|AcqQ-TarQ| × CBN		**0.7779***			**0.8799***	
		(2.6327)			**(2.7509)**	
CBN		0.3450***			0.5527***	
		(2.6856)			(4.1648)	
-|AcqQ-TarQ| × CBN_Recent			**0.8505**			**1.0268***
			(2.4470)			**(2.8396)**
CBN_Recent			0.3659***			0.5769***
			(2.6027)			(4.0080)
-|AcqQ-TarQ| × CBN_Old			**0.5069**			**0.2450**
			(0.9921)			**(0.4007)**
CBN_Old			0.2589			0.4610
			(0.9570)			(1.5980)
-|AcqQ-TarQ| × Same industry		0.3325**	0.3328**		0.2144	0.2137
		(2.1290)	(2.1321)		(1.3959)	(1.3923)
Same industry		0.8895***	0.8895***		0.3070***	0.3066***
		(8.9190)	(8.9192)		(3.8116)	(3.8095)
-|AcqQ-TarQ| × Ln(Acq_tar distance)		0.0019	0.0018		-0.0055	-0.0049
		(0.0483)	(0.0443)		(-0.1395)	(-0.1242)
Ln(Acq_tar distance)		-0.2610***	-0.2611***		-0.2372***	-0.2373***
		(-10.3471)	(-10.3489)		(-9.3116)	(-9.3161)
-|AcqQ-TarQ|	**0.9790***	**0.7515***	**0.7521***	**1.0188***	**0.9005***	**0.8962***
	(12.8366)	**(2.9236)**	**(2.9258)**	**(13.1180)**	**(3.5306)**	**(3.5166)**

Control variables:						
Ln(Acq outstanding loan)	0.1670***	0.1628***	0.1629***	0.2969***	0.2727***	0.2722***
	(4.5750)	(4.1805)	(4.1833)	(6.6323)	(5.8753)	(5.8659)
Ln(Acq assets)	0.1790***	0.1908***	0.1907***	0.0599***	0.0725***	0.0725***
	(12.0722)	(12.0389)	(12.0368)	(4.3801)	(5.0416)	(5.0399)
Ln(Acq Q)	0.3374***	0.2827***	0.2823***	0.4207***	0.4143***	0.4141***
	(4.3279)	(3.4861)	(3.4801)	(5.3740)	(5.2180)	(5.2180)
Acq past return	0.0785***	0.1020***	0.1017***	-0.1816***	-0.1825***	-0.1827***
	(2.9122)	(3.3332)	(3.3167)	(-5.2031)	(-4.9479)	(-4.9464)
Acq leverage	-1.7976***	-1.9861***	-1.9849***	-1.7823***	-1.8906***	-1.8864***
	(-7.1256)	(-7.6107)	(-7.6033)	(-7.4020)	(-7.5244)	(-7.5088)
Acq ROA	-0.0984	-0.2388	-0.2386	0.0361	-0.0813	-0.0835
	(-0.4756)	(-1.1024)	(-1.1012)	(0.1772)	(-0.3910)	(-0.4018)
Acq cash	-0.0682	-0.3709*	-0.3704*	0.0934	-0.0387	-0.0409
	(-0.3793)	(-1.9193)	(-1.9166)	(0.5409)	(-0.2179)	(-0.2302)
Ln(Acq firm age)	-0.2358***	-0.2003***	-0.2000***	-0.2191***	-0.2160***	-0.2156***
	(-6.4875)	(-5.2466)	(-5.2391)	(-6.0717)	(-5.7456)	(-5.7298)
Acq institution holding	-0.3616***	-0.3822***	-0.3814***	-0.1402	-0.1259	-0.1262
	(-3.8144)	(-3.9279)	(-3.9208)	(-1.4870)	(-1.3139)	(-1.3176)
Ln(Tar outstanding loan)	-0.0942**	-0.0832*	-0.0831*	-0.0833*	-0.1093**	-0.1093**
	(-2.3206)	(-1.8399)	(-1.8384)	(-1.7290)	(-2.1239)	(-2.1237)
Ln(Tar assets)	-0.2478***	-0.3046***	-0.3046***	-0.1747***	-0.2174***	-0.2170***
	(-15.3449)	(-16.2252)	(-16.1906)	(-8.7644)	(-10.1780)	(-10.1384)
Ln(Tar Q)	-0.3453***	-0.3833***	-0.3830***	-0.2938***	-0.3061***	-0.3045***
	(-4.8414)	(-5.2714)	(-5.2655)	(-4.2076)	(-4.3238)	(-4.2982)
Tar past return	0.0431	0.0311	0.0316	0.0295	0.0316	0.0319
	(1.5860)	(1.0084)	(1.0242)	(0.6395)	(0.6528)	(0.6593)
Tar leverage	0.6294***	0.6582***	0.6579***	0.6042***	0.6645***	0.6627***
	(2.9712)	(3.0157)	(3.0131)	(2.9519)	(3.1592)	(3.1469)
Tar ROA	-0.2709*	-0.2211	-0.2210	-0.0906	-0.0300	-0.0305
	(-1.6642)	(-1.3313)	(-1.3301)	(-0.5591)	(-0.1833)	(-0.1863)
Tar cash	-0.2578*	-0.3233**	-0.3242**	0.0141	-0.0202	-0.0209
	(-1.6694)	(-1.9990)	(-2.0036)	(0.0925)	(-0.1288)	(-0.1333)
Ln(Tar firm age)	0.1003***	0.1087***	0.1077***	0.1143***	0.1136***	0.1130***
	(2.7474)	(2.8240)	(2.7872)	(3.2576)	(3.1530)	(3.1347)
Tar institution holding	1.7352***	1.8564***	1.8563***	1.8311***	1.8753***	1.8737***
	(17.0304)	(16.8712)	(16.8583)	(17.5193)	(17.2931)	(17.2497)
Constant	-0.9205***	0.6404***	0.6430***	-0.7648***	0.6974***	0.6970***
	(-5.4596)	(2.6840)	(2.6922)	(-5.0861)	(3.0415)	(3.0401)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0648	0.107	0.107	0.0686	0.0954	0.0955
N	9,703	9,703	9,703	9,946	9,946	9,946

Table 3: Lending network size of CBN deals and search efficiency

This table report estimation results for a logit model. The dependent variable is a binary variable that takes the value of 1 for the actual sample merger deals and 0 for non-merger control deals constructed by matching each acquirer and target in an actual deal with non-merger firms. We use two alternative matching techniques as described in Table 2 to construct the control merger groups by matching up to five pairs of non-merger Compustat firms. The key explanatory variable is the triple-interaction term consisting of -|*AcqQ-TarQ*|, *CBN_Recent*, and *AcqBankNetwork*. *AcqBankNetwork-All borrowers* is a log-transformed count variable that equals the total number of all borrowers with outstanding loans from loan syndicates led by the same acquirers' lead banks, capturing the size of the banks' entire lending network. In generating *AcqBankNetwork-Target peers*, we only count the borrowers that are operating in the same sector (i.e., same two-digit SIC code) and of a similar size (i.e., the difference in market equity being within 10%) as the target firms, capturing the size of the target candidate pool in the lending network of the acquirers' banks. To save space, we do not report the estimates for other control variables. The stand-alone controls for *Acq outstanding loan* and *Tar outstanding loan* are included for estimation but the coefficients are not reported. All models include year fixed effects. See Appendix A for the detailed variable definitions. Student t-statistics from standard errors clustered by merger deal group is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Matching methods:	Matching 1	Matching 1	Matching 1	Matching 2	Matching 2	Matching 2
AcqBankNetwork is measuring:	All borrowers	Target peers	Target peers	All borrowers	Target peers	Target peers
-|AcqQ-TarQ| × CBN_Recent × AcqBankNetwork	**0.2498**	**0.5141***	**0.6400****	**0.0650**	**0.6609****	**0.7717*****
	(1.4663)	**(1.8996)**	**(2.3590)**	**(0.4529)**	**(2.3172)**	**(2.6741)**
-|AcqQ-TarQ| × AcqBankNetwork	0.0147	-0.1158	-0.1436	0.0300	-0.1079	-0.1818**
	(0.6013)	(-1.5343)	(-1.5652)	(1.2015)	(-1.4589)	(-2.0606)
CBN_Recent × AcqBankNetwork	0.0493	0.0963	0.1980*	0.0851***	0.2133*	0.2623**
	(1.4652)	(0.8580)	(1.7253)	(2.6044)	(1.9512)	(2.3573)
-|AcqQ-TarQ| × CBN_Recent	-0.9741	-0.0032	-0.6609	0.3472	-0.1597	-0.6772
	(-0.8514)	(-0.0051)	(-1.0253)	(0.3547)	(-0.2386)	(-0.9815)
CBN_Recent	-0.0103	0.2510	-0.1739	-0.1323	0.0889	-0.1321
	(-0.0464)	(0.8941)	(-0.5967)	(-0.6085)	(0.3217)	(-0.4600)
AcqBankNetwork	0.0105	-0.0875*	-0.0209	0.0777***	0.0959**	0.0716
	(0.4682)	(-1.8732)	(-0.3861)	(3.6995)	(2.1187)	(1.3746)
-|AcqQ-TarQ| × TarIndustryPeers			-0.2366***			-0.1099*
			(-3.5375)			(-1.8402)
TarIndustryPeers			-0.3176***			-0.0659*
			(-8.0058)			(-1.8996)
-|AcqQ-TarQ| × Acq outstanding loan			0.1577			0.2327**
			(1.3654)			(1.9965)
-|AcqQ-TarQ| × Tar outstanding loan			0.1846			0.1539
			(1.5396)			(1.3910)
-|AcqQ-TarQ| × Same industry	0.3477**	0.3126**	0.4750***	0.2418	0.1971	0.2769*
	(2.2009)	(1.9804)	(2.8791)	(1.5757)	(1.2721)	(1.8150)
Same industry	0.8968***	0.8904***	0.9805***	0.3207***	0.2827***	0.3077***
	(8.9036)	(8.8715)	(9.6663)	(3.9616)	(3.4663)	(3.8353)

-|AcqQ-TarQ| × Ln(Acq_tar distance)	-0.0002	0.0004	-0.0088	-0.0083	-0.0025	-0.0118
	(-0.0062)	(0.0101)	(-0.2222)	(-0.2104)	(-0.0632)	(-0.3021)
Ln(Acq_tar distance)	-0.2619***	-0.2614***	-0.2651***	-0.2403***	-0.2361***	-0.2407***
	(-10.3949)	(-10.3325)	(-10.4334)	(-9.4314)	(-9.2465)	(-9.4646)
-|AcqQ-TarQ|	0.7127***	0.8508***	1.5539***	0.8089***	0.9603***	1.1868***
	(2.6632)	(3.2104)	(4.2662)	(2.9802)	(3.6492)	(3.3163)
Constant	0.6254***	0.6267***	1.5686***	0.6838***	0.8442***	1.0234***
	(2.6072)	(2.5828)	(5.6037)	(2.9676)	(3.6192)	(3.8192)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.108	0.108	0.115	0.0972	0.0978	0.0990
N	9,703	9,703	9,703	9,946	9,946	9,946

Table 4: Search efficiency and merger announcement returns

The table reports estimation results from the OLS regressions of merger announcement returns on the common bank variables. The sample consists of 1,683 completed mergers during the 1992-2016 sample period. See Table 1 and Online Appendix B for the data filtering process and Appendix A for detailed variable descriptions. The respective dependent variables for Columns 1 (5, and 7), 2, and 3, *CombCAR3*, *AcqCAR3*, and *TarCAR3*, are cumulative three-day combined, acquirer, and target abnormal returns based on the Fama-French-Carhart four factor model. The dependent variable for Columns 4, 6, and 8, AcqGain3, is the acquirer's relative value gain over the three-day period surrounding the merger announcement date computed by dividing the acquirer's dollar gain net of the target's gain by the acquirer's and the target's combined pre-merger market equity. Models in all columns include year fixed effects and two-digit SIC industry fixed effects for both target and acquirer industries. Student t-statistics from standard errors double-clustered by acquirer and target industries is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	CombCAR3	AcqCAR3	TarCAR3	AcqGain3	CombCAR3	AcqGain3	CombCAR3	AcqGain3
CBN	**0.0145*** **	**0.0120*** **	**0.0136**	**0.0068***				
	(3.0159)	**(3.0453)**	**(0.8680)**	**(1.7801)**				
CBN_Recent					**0.0187*** **	**0.0092** **	**0.0175*** **	**0.0049**
					(3.8823)	**(2.3314)**	**(3.1790)**	**(1.2132)**
CBN_Old					-0.0087	-0.0066		
					(-0.8222)	(-1.3112)		
CBN_Recent × 100% stock							**0.0101**	**0.0235*** **
							(0.7121)	**(3.7394)**
Same industry	0.0036	0.0058**	-0.0169	0.0059**	0.0036	0.0059**	0.0036	0.0060**
	(1.6057)	(2.4406)	(-1.3735)	(2.1213)	(1.5806)	(2.1255)	(1.5680)	(2.2724)
Ln(Acq_tar distance)	-0.0005	-0.0006	-0.0012	-0.0000	-0.0004	0.0000	-0.0004	-0.0001
	(-0.6108)	(-0.6425)	(-0.7982)	(-0.0372)	(-0.5550)	(0.0078)	(-0.5817)	(-0.0899)
Control variables:								
100% stock	-0.0147***	-0.0131**	0.0276***	-0.0075	-0.0146***	-0.0074	-0.0159***	-0.0103**
	(-3.8082)	(-2.4942)	(2.8873)	(-1.4580)	(-3.9884)	(-1.4637)	(-4.0022)	(-2.1010)
100% cash	0.0186***	0.0222***	0.0717***	0.0148***	0.0189***	0.0149***	0.0186***	0.0143***
	(5.7697)	(7.4612)	(4.0917)	(3.6266)	(5.8724)	(3.6866)	(5.6052)	(3.5860)
Tender offer	0.0124***	0.0049	0.0448***	-0.0034	0.0123***	-0.0034	0.0123***	-0.0036
	(3.1849)	(1.3270)	(4.0366)	(-0.8590)	(3.2579)	(-0.8790)	(3.2198)	(-0.9076)
Toehold	0.0006	0.0024	0.0429*	-0.0039	0.0010	-0.0037	0.0010	-0.0035
	(0.0776)	(0.2674)	(1.7771)	(-0.4168)	(0.1291)	(-0.3958)	(0.1322)	(-0.3618)
Ln(Relative deal size)	0.0123***	-0.0215***	0.2601***	-0.0470***	0.0126***	-0.0469***	0.0126***	-0.0467***
	(3.2040)	(-6.6953)	(9.0587)	(-14.5664)	(3.2315)	(-14.3982)	(3.2111)	(-14.6299)
Common IB	0.0027	-0.0034	0.0075	-0.0044	0.0032	-0.0041	0.0029	-0.0046
	(0.2967)	(-0.3479)	(0.2983)	(-0.4731)	(0.3592)	(-0.4510)	(0.3267)	(-0.4908)
Ln(Acq outstanding loan)	0.0040	0.0037	-0.0156**	0.0041*	0.0039	0.0040*	0.0037	0.0039
	(1.2552)	(1.0331)	(-2.3752)	(1.7386)	(1.2022)	(1.7077)	(1.1824)	(1.6167)
Ln(Acq market equity)	0.0012	-0.0163***	0.2914***	-0.0298***	0.0014	-0.0297***	0.0015	-0.0293***
	(0.3069)	(-4.6118)	(9.8639)	(-10.1684)	(0.3683)	(-10.0299)	(0.3880)	(-10.2268)

Ln(Acq Q)	-0.0103	-0.0097	-0.0235**	-0.0049	-0.0103	-0.0049	-0.0103	-0.0049
	(-1.2420)	(-1.0807)	(-2.3841)	(-0.7539)	(-1.2445)	(-0.7545)	(-1.2507)	(-0.7503)
Acq leverage	-0.0147	-0.0098	-0.0333	-0.0076	-0.0149	-0.0078	-0.0153	-0.0083
	(-0.8970)	(-0.5763)	(-0.5929)	(-0.3669)	(-0.9349)	(-0.3732)	(-0.9647)	(-0.4135)
Acq past return	-0.0057	-0.0077	0.0006	-0.0061*	-0.0057	-0.0061*	-0.0057	-0.0060*
	(-1.1473)	(-1.2224)	(0.0680)	(-1.6845)	(-1.1569)	(-1.6826)	(-1.1446)	(-1.6675)
Acq ROA	0.0023	0.0045	0.0185	0.0061	0.0019	0.0058	0.0015	0.0047
	(0.1608)	(0.4481)	(0.3060)	(0.6976)	(0.1289)	(0.6578)	(0.1057)	(0.5265)
Ln(Acq firm age)	-0.0052**	-0.0043**	-0.0022	-0.0017	-0.0050**	-0.0016	-0.0052**	-0.0019
	(-2.3123)	(-1.9743)	(-0.2622)	(-0.8674)	(-2.2829)	(-0.8285)	(-2.3073)	(-0.9601)
Acq institution holding	-0.0018	-0.0050	0.0395	-0.0000	-0.0010	0.0004	-0.0014	-0.0003
	(-0.2447)	(-0.5397)	(1.6316)	(-0.0004)	(-0.1475)	(0.0613)	(-0.2067)	(-0.0370)
Ln(Tar outstanding loan)	-0.0032	-0.0022	-0.0023	-0.0023	-0.0031	-0.0022	-0.0035	-0.0026
	(-0.9948)	(-0.5976)	(-0.2617)	(-0.7629)	(-0.9783)	(-0.7619)	(-1.1608)	(-0.9181)
Ln(Tar market equity)	-0.0081**	0.0099**	-0.2951***	0.0272***	-0.0083**	0.0270***	-0.0084**	0.0267***
	(-2.0716)	(2.3090)	(-9.7623)	(8.9391)	(-2.0994)	(8.7900)	(-2.1413)	(9.0009)
Ln(Tar Q)	0.0010	0.0070	-0.0614***	0.0100***	0.0010	0.0101***	0.0012	0.0103***
	(0.1246)	(1.0583)	(-5.9926)	(4.4463)	(0.1334)	(4.6504)	(0.1585)	(5.0166)
Tar leverage	-0.0017	0.0341**	-0.2433***	0.0630***	-0.0012	0.0633***	-0.0016	0.0626***
	(-0.0959)	(1.9938)	(-8.4473)	(7.6265)	(-0.0718)	(8.0131)	(-0.0897)	(7.8327)
Tar past return	0.0000	0.0036	-0.0187	0.0052*	0.0001	0.0052*	-0.0000	0.0051*
	(0.0004)	(0.7343)	(-1.6269)	(1.7776)	(0.0126)	(1.7880)	(-0.0000)	(1.7273)
Tar ROA	0.0111	-0.0137	0.0018	-0.0217**	0.0107	-0.0220**	0.0111	-0.0215**
	(0.6662)	(-0.8433)	(0.0345)	(-2.1820)	(0.6401)	(-2.2196)	(0.6587)	(-2.1538)
Ln(Tar firm age)	0.0054	0.0036	0.0072	0.0008	0.0056*	0.0010	0.0055*	0.0008
	(1.5864)	(1.0485)	(0.9221)	(0.2961)	(1.6878)	(0.3547)	(1.6592)	(0.3066)
Tar institution holding	0.0140***	0.0131*	0.0214	-0.0004	0.0135***	-0.0007	0.0136***	-0.0008
	(3.1628)	(1.7944)	(0.9759)	(-0.0429)	(2.9068)	(-0.0749)	(2.8471)	(-0.0897)
Constant	0.1320***	0.1112***	-0.2704***	0.0469**	0.1301***	0.0458**	0.1325***	0.0489**
	(4.8996)	(3.3159)	(-4.0051)	(2.1106)	(4.9143)	(2.0768)	(4.9305)	(2.2459)
Acquirer Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.1455	0.1100	0.3587	0.2015	0.1475	0.2019	0.1476	0.2039
N	1,683	1,683	1,683	1,683	1,683	1,683	1,683	1,683

Table 5: Factor analysis on proxies for information asymmetry

This table reports the results from the factor analysis on the seven information proxies for both acquirers and targets in the 1,683 sample merger deals. For the acquirers and the targets, the first three columns (i.e., Factor 1 through 3) report the factor loadings of the seven proxies for the respective factors. The first four proxies (i.e., number of analysts, firm age, firm size, and tangibility) measure the degree of information symmetry, whereas the last three (i.e., idiosyncratic volatility, bid-ask spread, and abnormal accruals) measure the severity of information asymmetry. The table reports the predicted signs for the factor loadings of the seven proxies, with an assumption that the underlying common variations reflect information asymmetry. The columns labeled KMO report the Kaiser-Meyer-Olkin (KMO) sampling adequacy index scores for the proxies at both the individual proxies and collective levels. Finally, the bottom row reports the factors' eigenvalues, which reflect the extent of common variations within the proxies captured by each factor.

Variable	Predicted sign	Acquirers				Targets			
		Factor 1	Factor 2	Factor 3	KMO	**Factor 1**	Factor 2	Factor 3	KMO
Number of analysts	-	**0.5249**	0.4131	-0.0061	0.7297	**0.5358**	-0.3885	0.1354	0.6779
Firm age	-	**0.6372**	-0.1970	0.1415	0.7961	**0.4732**	0.2599	0.0667	0.7987
Firm size	-	**0.8316**	0.0144	0.1132	0.7669	**0.8071**	0.0214	0.1704	0.7455
Tangibility	-	**0.1254**	-0.4000	0.0783	0.6006	**0.1891**	0.4294	0.1681	0.5117
Idiosyncratic volatility	+	**-0.7501**	0.2600	0.1073	0.7451	**-0.7531**	-0.1905	0.2030	0.6939
Bid-ask spread	+	**-0.6368**	-0.3668	0.0768	0.7324	**-0.7027**	0.3433	0.1218	0.6741
Abnormal accruals	+	**-0.3057**	0.2999	0.2012	0.6747	**-0.2599**	-0.3251	0.1345	0.6137
KMO overall					0.7455				0.6958
Eigenvalues		**2.4505**	0.6617	0.0969		**2.3266**	0.6632	0.1542	

Table 6: Alternative explanations – are the results driven by information asymmetry?

Panel A of this table reports estimation results for Eq. (7) augmented with the control variables for information asymmetry. The dependent variable is a binary variable that takes the value of 1 for the actual sample merger deals and 0 for control merger deals constructed by matching each acquirer and target in an actual deal with non-merger firms. We use two alternative matching techniques as described in Table 2 to construct the control merger groups by matching up to five pairs of non-merger Compustat firms. The key explanatory variable is the interaction terms between -|*AcqQ-TarQ*| and *CBN_Recent*. The measure of information asymmetry, *Acq_info_asymmetry* and *Tar_info_asymmetry*, are constructed using the first factors stemming from the factor analysis approach described in Table 5, but implemented on the matched samples. For the tests in Columns 1 and 2 (Columns 3 and 4), we match non-merger control deals on the full merger sample (a subsample only including *CBN_Recent*, overlapping, and expired CBN deals, which henceforth is called *Comparable quality sample*). The firms in the matched hypothetical deals are required to take loan facilities from the same banks that lend to the acquirers and the targets in the merged deals before merger announcement. All models include the control variables (coefficients not reported) in Table 2 and year fixed effects. Student t-statistics from standard errors clustered by merger deal group is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively. Columns 1 and 2 (Columns 3 and 4) in Panel B reports estimation results of Eq. (10) augmented with the control variables for information asymmetry on the 1,683 merger sample (Comparable quality subsample). The models in the panel use two alternative dependent variables: *CombCAR3* and *AcqGain3*. *CombCAR3* is the acquirer's and the target's combined cumulative three-day abnormal returns surrounding the announcement date. AcqGain3 is the acquirer's relative value gain over the three-day period surrounding the announcement date. All models include all of the deal and firm control variables (coefficients not reported) in Table 4 as well as year and two-digit SIC industry fixed effects for both target and acquirer industries. See Appendix A for the detailed variable definitions. Student t-statistics from standard errors double-clustered by acquirer and target industries is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Merger likelihood

	(1)	(2)	(3)	(4)
Matching methods:	Matching 1	Matching 2	Matching 1	Matching 2
Treated merger group:	Full sample	Full sample	Comparable quality	Comparable quality
-|AcqQ-TarQ| × CBN_Recent	**0.8054****	**0.8272****	**0.8560****	**0.8192****
	(2.1097)	**(2.0775)**	**(2.1386)**	**(1.9744)**
-|AcqQ-TarQ|	0.7769***	0.9775***	2.5464***	2.4038***
	(2.9439)	(3.7752)	(3.4233)	(2.9454)
CBN_Recent	0.3337**	0.4605***	-0.6970***	-0.7164***
	(2.1479)	(2.9532)	(-3.7028)	(-3.8122)
-|AcqQ-TarQ| × Acq_info_asymmetry	-0.0342	-0.1403*	-0.0673	-0.1205
	(-0.3772)	(-1.7286)	(-0.2736)	(-0.4533)
Acq_info_asymmetry	0.1280	-0.3676***	-0.2691	-0.3593
	(0.9826)	(-2.9474)	(-1.0707)	(-1.4301)
-|AcqQ-TarQ| × Tar_Info_asymmetry	-0.0334	-0.0206	-0.2240	-0.2258
	(-0.3894)	(-0.2564)	(-1.0145)	(-0.9797)
Tar_Info_asymmetry	0.1326	0.0880	0.1818	0.0436
	(1.2313)	(0.7861)	(0.8669)	(0.1918)
-|AcqQ-TarQ| × Same industry	0.3156**	0.2351	-0.3595	-0.9535*
	(1.9734)	(1.5073)	(-0.7083)	(-1.8016)
Same industry	0.8495***	0.3054***	0.6627***	0.7176***
	(8.3571)	(3.6957)	(3.5478)	(3.6894)
-|AcqQ-TarQ| × Acq-tar distance	0.0053	-0.0109	-0.2102*	-0.1501
	(0.1292)	(-0.2709)	(-1.8311)	(-1.2429)
Acq-tar distance	-0.2533***	-0.2356***	-0.2445***	-0.2197***
	(-9.8736)	(-9.0821)	(-5.0026)	(-4.2241)
Constant	0.5833	1.8986***	-0.9377	0.3494
	(0.9536)	(3.2810)	(-0.7707)	(0.2799)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Pseudo R^2	0.106	0.0951	0.182	0.188
Observations	9,182	9,382	2,726	2,717

Panel B: Announcement return

	(1)	(2)	(3)	(4)
Dependent variable:	CombCAR3	AcqGain3	CombCAR3	AcqGain3
Sample used:	Full sample	Full sample	Comparable quality	Comparable quality
CBN_Recent	**0.0192***	**0.0080**	**0.0241***	**0.0100**
	(4.2051)	**(2.0398)**	**(3.9681)**	**(2.1621)**
Acq_Info_asymmetry	-0.0059	0.0079	-0.0381*	0.0025
	(-0.8244)	(0.6592)	(-1.6904)	(0.0966)
Tar_info_asymmetry	0.0121*	0.0179***	0.0421**	0.0278*
	(1.8392)	(2.6715)	(2.1961)	(1.7735)
Same industry	0.0033	0.0061*	-0.0054	-0.0036
	(1.5788)	(1.9529)	(-0.7114)	(-0.5738)
Ln(Acq-tar distance)	-0.0003	0.0002	-0.0009	-0.0005
	(-0.3663)	(0.3090)	(-0.9730)	(-0.2844)
Constant	0.0764*	-0.0834	0.3782***	-0.2338
	(1.8309)	(-1.0078)	(3.5224)	(-1.6134)
Control variables	Yes	Yes	Yes	Yes
Acquirer Industry FE	Yes	Yes	Yes	Yes
Target Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.1467	0.2143	0.2904	0.2830
N	1,625	1,625	469	469

Table 7: Search efficiency and post-merger long-term operating performance

This table presents matched group-adjusted long-term operating performance of merged firms by each subgroup during first two-year period following deal completion. Two post-merger operating performance measures employed for the test are changes in return on assets (Δ*ROA[0,+1]* and Δ*ROA[0,+2]*) and asset turnover (Δ*ATover[0,+1]* and Δ*ATover[0,+2]*) over one- and two-year periods starting the first fiscal end date immediately after merger completion date. See Section 4.4 in the main text for the detailed procedure to generate the measures. Panel A reports the results based on the nearest-neighbor matching and Panel B reports the results based on the propensity-score matching. Columns 1, 2 and 3 of each panel report the mean performance of the CBN_Recent group, the non-CBN group, and the subset of the non-CBN group comprising only the overlapping and expired CBN deals, respectively. Column 4 (Column 5) reports the mean-difference test results between CBN_Recent and the non-CBN group (CBN_Recent and the comparator subsets of the non-CBN group). ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Control group-adjusted performance, based on nearest-neighbor matching

	(1) CBN deals	(2) Non-CBN deals (All)	(3) Non-CBN deals (Comparator sets)	(4) Mean Diff. (1)-(2)	(5) Mean Diff. (1)-(3)
ΔROA[0,+1]yrs	0.016***	0.008***	0.013**	0.008	0.004
	(0.000)	(0.001)	(0.014)	(0.224)	(0.566)
ΔROA[0,+2]yrs	0.027***	-0.000	0.009	0.027***	0.018**
	(0.000)	(0.984)	(0.100)	(0.001)	(0.019)
ΔATover[0,+1]yrs	0.112***	0.067***	0.054***	0.045**	0.058**
	(0.000)	(0.000)	(0.002)	(0.026)	(0.016)
ΔATover[0,+2]yrs	0.119***	0.058***	0.030	0.061**	0.090***
	(0.000)	(0.000)	(0.214)	(0.037)	(0.008)

Panel B: Control group-adjusted performance, based on propensity score matching

	(1) CBN deals	(2) Non-CBN deals (All)	(3) Non-CBN deals (Comparator sets)	(4) Mean Diff. (1)-(2)	(5) Mean Diff. (1)-(3)
ΔROA[0,+1]yrs	0.018***	0.005*	0.010**	0.014*	0.008
	(0.000)	(0.070)	(0.035)	(0.058)	(0.226)
ΔROA[0,+2]yrs	0.032***	0.001	0.013**	0.031***	0.019**
	(0.000)	(0.707)	(0.012)	(0.000)	(0.018)
ΔATover[0,+1]yrs	0.098***	0.056***	0.072***	0.042**	0.025
	(0.000)	(0.000)	(0.000)	(0.047)	(0.309)
ΔATover[0,+2]yrs	0.109***	0.050***	0.046**	0.059**	0.063**
	(0.000)	(0.000)	(0.037)	(0.049)	(0.048)

Table 8: Banks' participation and post-merger changes in asset volatility

The table reports the OLS model estimation of the changes between pre- and post-merger asset volatility on pre-merger connections through CBNs. The dependent variable for Columns 1 and 2, Δ *Asset volatility 1*, is the measure of pre- and post-merger asset volatility changes constructed only using the pre-merger data of acquirers and targets. The dependent variable for Columns 3 and 4, Δ *Asset volatility 2*, is the measure of pre- and post-merger asset volatility changes constructed using both the pre-merger announcement data from acquirers and targets and the post-merger data from the merged firm. Columns 1 and 3 show the results based on the full sample, while Columns 2 and 4 show the results based on the comparable quality sample, which comprises CBN_Recent, expired CBN, and overlapping merger deals. See Appendix D for a detailed description of the variable construction process. Student t-statistics from standard errors double-clustered by acquirer and target industries is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Dependent variable:	(1) Δ Asset volatility 1	(2) Δ Asset volatility 1	(3) Δ Asset volatility 2	(4) Δ Asset volatility 2
Sample used:	Full sample	Comparable quality	Full sample	Comparable quality
CBN_Recent	**-0.0077***	**-0.0015**	**-0.0415**	**-0.0081**
	(-1.6632)	**(-0.1955)**	**(-1.3803)**	**(-0.1558)**
Constant	-0.1597***	0.0133	0.3387**	0.2701
	(-9.0652)	(0.3267)	(2.2475)	(1.3432)
Acquirer Industry FE	Yes	Yes	Yes	Yes
Target Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0887	0.1089	0.1481	0.1950
N	1,655	479	1,558	456

Table 9: Banks' participation and post-merger changes in loan spreads

The table reports estimation results from the OLS regressions of credit spread on *CBN_Recent* before and after consummation of the sample merger deals. The dependent variable for all columns is Ln(ALLINDRAWN), the log-transformed ALLINDRAWN, which is the spread over LIBOR plus the transaction fee determined at the time of loan origination. Column 1 (column 2) shows the results based on all loan facilities extended to the sample acquirers (targets) during the 365 day-period that ends one day prior to the merger announcement date. Column 3 shows the result based on all loan facilities extended to the merged firms during the 365-day period that begins one day *after* the merger completion date. In constructing the sample for the test in Column 3, we ensure to only include the records where the fiscal end date of the corresponding COMPUSTAT observation for each loan record is dated after the merger completion date such that the firm-specific values are updated to reflect the post-merger conditions. For the test in Column 4, each borrower in the sample is required to appear in the acquirer group both during the pre-period and also during the post-period. Each of the models in Columns 1, 2, and 3 (The model in Column 4) includes controls for industry (deal), year, and loan type fixed effects. Student t-statistics from standard errors clustered by firm is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Sample used:	Acquirer	Target	Merged firm	Acquirer-Merged
Time period:	Pre-merger	Pre-merger	Post-merger	Pre-Post
CBN_Recent × Post_merger				**-0.1985****
				(-2.0878)
Post_merger				-0.1587
				(-1.1194)
CBN_Recent	**-0.0415**	**-0.0478**	**-0.2071****	
	(-0.6794)	**(-0.4704)**	**(-2.1800)**	
Log(Facility amount)	-0.2037***	-0.0473	-0.0604*	-0.1203***
	(-5.5292)	(-1.5414)	(-1.8091)	(-2.7466)
Log(Maturity)	-0.0116	0.0253	-0.0747	-0.0964*
	(-0.1693)	(0.4020)	(-0.8182)	(-1.7735)
Log(Covenant count)	0.0385	-0.0851	0.2518***	0.1496*
	(0.6647)	(-1.0345)	(2.9922)	(1.7122)
Log(Lender count)	0.0766**	-0.0726*	-0.0289	-0.0035
	(2.2124)	(-1.6775)	(-0.6826)	(-0.0915)
Secured	0.4146***	0.3834***	0.5065***	0.1930**
	(6.6877)	(3.6297)	(5.1814)	(2.5368)
Performance pricing	0.0055	-0.0083	0.0533	-0.0503
	(0.0906)	(-0.0960)	(0.6692)	(-0.8898)
Log(Assets)	-0.1091***	-0.1480***	-0.1097**	-0.1798
	(-2.9716)	(-2.8914)	(-2.2964)	(-1.5686)
ROA	-1.6695***	-1.8337***	-0.5367	-1.2344
	(-4.6659)	(-3.8475)	(-1.0249)	(-1.0562)
Cash holdings	0.1530***	-0.0161	0.1526	0.0393
	(3.1601)	(-0.6144)	(1.1850)	(1.2579)
Leverage	0.9837***	1.2739***	1.6852***	0.0896
	(3.8937)	(4.3978)	(5.3723)	(0.1810)
Tangibility	0.0788	-0.0272	-0.1060	-0.6254
	(0.3518)	(-0.1203)	(-0.2836)	(-0.9734)
Rated	0.1129	0.0950	-0.0601	0.1304
	(1.4691)	(0.7458)	(-0.5239)	(1.0232)
Constant	8.7510***	6.4122***	6.8181***	8.8832***
	(15.4214)	(10.7293)	(8.2640)	(8.2759)
Deal FE	No	No	No	Yes
Industry FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Loan type FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.7210	0.7933	0.7986	0.9031
N	998	388	507	580

Online Appendix A: Additional proofs of propositions

The online appendix contains proof of Lemma 2 in Appendix E, as well as the technical details of the PDEs as well as the solutions in the proof of Proposition 1.

Proof of Lemma 2:

We first define the value function of acquirer and candidate target in the bargaining round n as $\pi_n^A(s)$ and $\pi_n^B(s)$, where the s, which could be offered from either party, is the share of synergy obtained by the acquirer. Since the acquirer and candidate exchange the offers, we mark the acquirer's offer as s_A, and candidate's offer as s_B. The value function measures the present value of the amount of merger synergy, discounted by the interest rate r back to $t = 0$, the *beginning* of the bargaining process.

After the acquirer starts the bargaining by first offering a s_A, the candidate firm, at ϵ time after the beginning of the first round, can either reject the offer and make a counteroffer or accepts the offer immediately. The acceptance of the offer leads to a realization of merger synergy $\mu = \overline{\mu}(1 - |\theta_A - \theta_B|)$ at ϵ time after the start of the bargain. The candidate, conditional on receiving the offer at time ϵ, obtains a present value of $\pi_1^t(s_A) = e^{-\epsilon r}\mu(1 - s_A)$, where $e^{-\epsilon r}$ to the represent the discount due to the bargaining time. The acquirer, however, obtains a present value of $\pi_1^A(s_A) = \left(1 - e^{-\epsilon/\kappa}\right)e^{-\epsilon r}V(\theta_A) + e^{-\epsilon/\kappa}e^{-\epsilon r}\mu s_A$, since there is a probability that she meets with a new candidate before ϵ, a probability $\Pr(\tau < \epsilon) = 1 - e^{-\epsilon/\kappa}$ event upon which the bargaining gets canceled and the acquirer left with outside value $V(\theta_A)$.

If the candidate decided to give a counteroffer instead, the expected gain of the candidate offering at the second round is $\pi_2^B(s_B) = e^{-\epsilon/\kappa}e^{-2\epsilon r}\mu(1 - s_B)$. Similarly, there is a probability $\Pr(\tau < \epsilon) = 1 - e^{-\epsilon/\kappa}$ event upon which the bargaining gets canceled and the candidate left no synergy gain at all.

In case there is no new arrival of candidates, the acquirer, who faces the candidate's second round with a value $\pi_2^A(s_B) = e^{-2\epsilon r}\mu s_B$. She decides whether to accept the offer or counter it in the third round. Similar analysis gives us the present value of the expected gain of the counter-offer as $\pi_3^A(s_A) = \left(1 - e^{-\epsilon/\kappa}\right)e^{-3\epsilon r}V(\theta_A) + e^{-\epsilon/\kappa}e^{-3\epsilon r}\mu s_A$.

In equilibrium, both the acquirer and the candidate are indifferent between accepting the offer and countering the offer. In other words, we have

$$\pi_1^B(s_A) = \pi_2^B(s_B)$$

$$\pi_2^A(s_B) = \pi_3^A(s_A)$$

Or

$$e^{-\epsilon r}\mu(1 - s_A) = e^{-\epsilon/\kappa}e^{-2\epsilon r}\mu(1 - s_B)$$

$$e^{-2\epsilon r}\mu s_B = \left(1-e^{-\epsilon/\kappa}\right)e^{-3\epsilon r}V(\theta_A) + e^{-\epsilon/\kappa}e^{-3\epsilon r}\mu s_A$$

Which gives us

$$\left(1-e^{-2\epsilon(1/\kappa+r)}\right)\mu s_A = \left(1-e^{-\epsilon(1/\kappa+r)}\right)\mu + e^{-\epsilon(2r+1/\kappa)}\left(1-e^{-\epsilon\lambda}\right)V(\theta_A)$$

When ϵ is small, i.e., $\epsilon \downarrow 0$,we have $e^{\epsilon x} = 1-\epsilon x$. Therefore, we have the acquirer and target's shares of merger synergy as $s_A = \frac{1}{2} + \frac{V(\theta_A)}{2\kappa\mu}$, and $s_B = \frac{1}{2} - \frac{V(\theta_A)}{2\kappa\mu}$.

In other words, the acquirer can obtain a larger share of synergy s_A if her search cost κ is lower, or she has better the outside option $V(\theta_A)$. In equilibrium, the acquirer proposes s_A, and the candidate accepts it in the first round: counter offering gives out the same amount of value, and further rounds of counter offering lead to the same share of synergy whereas the present value gets discounted more due to the time spent in bargaining. Hence, the equilibrium offer is

$s(\theta_A, \theta_B, V(\theta_A)) = s_A = \frac{1}{2} + \frac{V(\theta_A)}{2\overline{\mu}\kappa(1-|\theta_A-\theta_B|)}$.

Additional Technical Details for Proof of Proposition1:

We further illustrate the solution of the bank debt value. Consider a delta-hedged portfolio of bank debt $f^i(V^i, t)$ and underlying firm value V^i with value $f^i - \frac{\partial f^i}{\partial V^i}V^i$ is risk-free, for both the acquirer where $i = A$, and the target where $i = B$. Since a perfect delta-hedging portfolio is risk-free, it must earn riskless return r by non-arbitrage argument. Apply Ito's lemma to the value of the portfolio gives us the bank debt f^i follows a parabolic PDE $\frac{\partial f^i}{\partial t} + \frac{1}{2}\frac{\partial^2 f^i}{\partial {V^i}^2}\sigma^2 = rf^i$, with boundary condition $f^i = min(e^{rT}D_0^i, V_T^i)$ at $t = T$. The solution of the PDE gives the value of bank debt at time $t = 0$ to be

$$V_0^i - \left[V_0^i - D_0^i\right]\Phi\left(\delta^i\right) - \frac{\sqrt{T}}{\sqrt{2\pi}}\sigma e^{-rT-\frac{\delta^{i2}}{2}}$$

where $\delta^i = \frac{e^{rT}(V_0^i - D_0^i)}{\sigma\sqrt{T}}$.

Similarly, the fair value of post-merger bank debt f^M follows the same parabolic PDE $\frac{\partial f^M}{\partial t} + \frac{1}{2}\frac{\partial^2 f^M}{\partial {V^M}^2}\sigma'^2 = rf^M$, with a different boundary condition $f^M = min(e^{rT}(D_0^A + D_0^B), V_T^M)$ at $t = T$. Solving this PDE gives us the present value of post-merger bank debt at $t = 0$ to be

$$V_0^M - [V_0^M - (D_0^A + D_0^B)]\Phi(\delta') - \frac{\sqrt{T}}{\sqrt{2\pi}}\sigma' e^{-rT-\frac{\delta'^2}{2}}$$

where $\delta' = \frac{e^{rT}(V_0^M - (D_0^A + D_0^B))}{\sigma'\sqrt{T}}$, and $V_0^M = V_0^A + V_0^B + \mu(\theta_A, \theta_B)$.

The value of loan portfolio change before and after the bank's participation in searching is the integral of bank loans over types of candidates with $\theta_B \in \Theta_B(\theta_A) = \{\theta_B : |\theta_A - \hat{\theta}_B^*(\theta_A)| \leq |\theta_A - \theta_B| \leq |\theta_A - \theta_B^*(\theta_A)|\}$, which gives us

$$\hat{\Pi}(\hat{\theta}_B^*, \sigma') - \Pi(\theta_B^*, \sigma')$$
$$= \int_{\Theta_B(\theta_A)} \mu(\theta_A, \theta_B)\Phi(-\delta') - \frac{\sqrt{T}}{\sqrt{2\pi}}\sigma' e^{-rT-\frac{\delta'^2}{2}}$$
$$+ \sum_{i\in\{A,B\}} [D_0^i - V_0^i][\Phi(\delta') - \Phi(\delta^i)] + \frac{\sqrt{T}}{\sqrt{2\pi}}\sigma e^{-rT-\frac{\delta^{i2}}{2}}$$

in the proof of Proposition 1.

Online Appendix B: Data construction

Steps	Actions taken for data screening	Remaining obs. after each action
1	Start with raw SDC transactions involving acquirers and targets from 1992 to 2016 with CRSP entry	25,704
2	Exclude repurchases, recapitalizations, minority share purchases, exchange offers, spin-offs, subsidiary transactions, and privatizations	5,000
3	Exclude incomplete deals, deals with the acquirer's pre-deal target ownership being equal to or greater than 50%, and deals with post-deal ownership being less than 100%	3,682
4	Exclude deals with deal value less than $1 million or with the relative size of deal value to market value of acquirers measured seven days before announcement less than 1%	3,400
5	Exclude deals involving firms with headquarter locations outside the US, firms with CRSP share code other than 10 or 11, and firms with exchange code other than 1, 2, or 3 (NYSE, AMEX or NASDAQ)	2,843
6	Exclude deals with the target SIC code indicating financial (6000s) or utility (4949-4999s) industries, and deals with missing values for announcement return, firm, industry and deal characteristics in the baseline regression model (see Appendix A for variable definitions)	1,683

Online Appendix C: Bank network and search cost

This table presents estimation results for a logit model. The dependent variable is a binary variable that takes the value of 1 for the actual sample merger deals and 0 for control merger deals constructed by matching each acquirer and target in an actual deal with non-merger firms. We use two alternative matching techniques as described in Table 2 to construct the control merger groups by matching up to five pairs of non-merger Compustat firms. The key explanatory variable is the triple-interaction term consisting of -|AcqQ-TarQ|, CBN_Recent, and TarBankNetwork. TarBankNetwork-All borrowers is a log-transformed count variable that equals the total number of all borrowers with outstanding loans from loan syndicates led by the same targets' lead banks, capturing the size of the banks' entire lending network. In generating TarBankNetwork-Target peers, we only count the borrowers that are operating in the same sector (i.e., same two-digit SIC code) and in similar size (i.e., the difference in market equity being within 10%) as the acquirer firms, capturing the size of the acquirer candidate pool in the lending network of the targets' banks. To save space, we do not report the estimates for other control variables. All models include year fixed effects. See Appendix A for the detailed variable definitions. Student t-statistics from standard errors clustered at the deal level is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Matching methods:	Matching 1	Matching 1	Matching 2	Matching 2
Target bank network variable:	All borrowers	Acquirer peers	All borrowers	Acquirer peers
-|AcqQ-TarQ| × CBN_Recent × TarBankNetwork	**0.3528**	**0.3871**	**0.4241**	**0.1986**
	(0.9550)	**(1.0388)**	**(0.9817)**	**(0.5521)**
-|AcqQ-TarQ| × TarBankNetwork	0.0439	0.0883	0.0470	0.1279
	(1.3075)	(0.7202)	(1.4838)	(1.0863)
CBN_Recent × TarBankNetwork	-0.2096	-0.1839	-0.1488	-0.0536
	(-1.3334)	(-1.2004)	(-0.9631)	(-0.3681)
-|AcqQ-TarQ| × CBN_Recent	-1.7353	-0.0621	-2.0309	0.4324
	(-0.7078)	(-0.0794)	(-0.7016)	(0.5538)
CBN_Recent	1.6819	0.8294**	1.4751	0.6757**
	(1.6193)	(2.4856)	(1.4445)	(2.0927)
-|AcqQ-TarQ|	0.7978***	0.8326***	0.8576***	0.8930***
	(9.1430)	(9.9678)	(9.6838)	(10.6042)
TarBankNetwork	-0.0312	-0.0745	-0.0323	-0.0450
	(-1.2756)	(-1.0885)	(-1.3107)	(-0.6553)
Constant	0.6131***	0.6395***	0.6181***	0.6127***
	(2.9050)	(3.0430)	(3.2545)	(3.2002)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.107	0.109	0.0969	0.0959
N	9,703	9,703	9,946	9,946

Online Appendix D: Sensitivity tests on the effect of the 14 proxies for asymmetric information

This online appendix reports the results from the sensitivity tests based on Eq. (7) using each of the 14 proxies for information asymmetry, which we employ to perform the factor analysis as reported in Table 5. The test sample consists of the actual merger deals and the propensity score-matched hypothetical deals discussed in Table 2.

Panel A: Information asymmetry for acquirers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
-|AcqQ-TarQ| × CBN_Recent	**0.9168****	**0.9169****	**0.8957****	**0.8648****	**0.9192****	**0.9593*****	**0.9937*****
	(2.4855)	**(2.5140)**	**(2.4797)**	**(2.3196)**	**(2.4974)**	**(2.6631)**	**(2.6881)**
-|AcqQ-TarQ|	0.7182**	1.1179***	0.9780***	0.4238	0.5820*	0.7794***	0.9084***
	(2.5564)	(4.1187)	(3.7352)	(1.1891)	(1.7443)	(2.9839)	(3.5292)
CBN_Recent	0.5049***	0.5116***	0.5061***	0.4831***	0.5037***	0.5176***	0.5231***
	(3.4626)	(3.5290)	(3.5157)	(3.2764)	(3.4514)	(3.5874)	(3.5751)
-|AcqQ-TarQ| × Acq Analysts	0.0994						
	(1.6236)						
Acq Analysts	-0.1016**						
	(-2.2468)						
-|AcqQ-TarQ| × Acq Idiosyncratic volatility		-6.9069*					
		(-1.9582)					
Acq Idiosyncratic volatility		-12.6693***					
		(-3.9562)					
-|AcqQ-TarQ| × Acq BidAsk spread			-2.2057				
			(-0.5386)				
Acq BidAsk spread			-10.5525***				
			(-3.7309)				
-|AcqQ-TarQ| × Acq Firm size				0.0686**			
				(1.9919)			
Acq Firm size				0.1055***			
				(4.9400)			
-|AcqQ-TarQ| × Acq Firm age					0.1208		
					(1.4847)		
Acq Abnormal accrual					-0.1637***		
					(-3.2874)		
-|AcqQ-TarQ| × Acq Tangibility						0.8070**	
						(2.1126)	
Acq Tangibility						-0.2183	
						(-1.2502)	
-|AcqQ-TarQ| × Acq Abnormal accrual							-0.0017
							(-0.3988)
Acq Abnormal accrual							0.0006
							(0.1582)
-|AcqQ-TarQ| × Same industry	0.2322	0.2608*	0.2125	0.2735*	0.2616*	0.2391	0.1993

	(1.5032)	(1.7227)	(1.3642)	(1.7631)	(1.7019)	(1.5790)	(1.2931)
Same industry	0.3235***	0.3311***	0.2992***	0.3337***	0.3278***	0.3421***	0.2913***
	(4.0123)	(4.1338)	(3.6559)	(4.1082)	(4.0765)	(4.2720)	(3.5896)
-|AcqQ-TarQ| × Acq-tar distance	-0.0014	-0.0070	-0.0106	-0.0036	-0.0044	-0.0099	-0.0019
	(-0.0357)	(-0.1811)	(-0.2605)	(-0.0928)	(-0.1134)	(-0.2522)	(-0.0469)
Acq-tar distance	-0.2359***	-0.2394***	-0.2362***	-0.2372***	-0.2374***	-0.2415***	-0.2337***
	(-9.2569)	(-9.4498)	(-9.1405)	(-9.3592)	(-9.3717)	(-9.5215)	(-9.1150)
Constant	0.4702**	1.3596***	1.5250***	0.4539*	0.5394**	0.7146***	0.6746***
	(2.0015)	(4.7455)	(4.7077)	(1.7936)	(2.2256)	(3.1008)	(2.9031)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0969	0.0965	0.0962	0.0955	0.0953	0.0966	0.0949
N	9,931	9,931	9,773	9,931	9,931	9,931	9,722

Panel B: Information asymmetry for targets

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
-|AcqQ-TarQ| × CBN_Recent	**1.0613*** **	**0.9188** **	**1.0266*** **	**0.9346** **	**0.8052** **	**0.9595*** **	**0.9751*** **
	(2.7561)	**(2.5052)**	**(2.8067)**	**(2.5252)**	**(2.0877)**	**(2.6778)**	**(2.6583)**
-|AcqQ-TarQ|	0.9613***	1.1068***	0.8913***	0.6400**	0.5482*	0.7925***	0.9657***
	(3.6389)	(3.9586)	(3.4394)	(2.0710)	(1.6802)	(3.1069)	(3.7416)
CBN_Recent	0.5263***	0.4914***	0.5509***	0.5090***	0.4566***	0.5199***	0.5246***
	(3.4519)	(3.3605)	(3.7790)	(3.4611)	(2.9861)	(3.6068)	(3.6036)
-|AcqQ-TarQ| × Tar Analysts	-0.0608						
	(-0.8573)						
Tar Analysts	0.1567***						
	(2.9663)						
-|AcqQ-TarQ| × Tar Idiosyncratic volatility		-3.9451					
		(-1.5308)					
Tar Idiosyncratic volatility		3.2710					
		(1.3907)					
-|AcqQ-TarQ| × Tar BidAsk spread			1.6610				
			(0.7820)				
Tar BidAsk spread			0.0979				
			(0.0561)				
-|AcqQ-TarQ| × Tar Firm age				0.1158			
				(1.4463)			
Tar Firm age				0.1653***			
				(3.2067)			
-|AcqQ-TarQ| × Tar Firm size					0.0733*		
					(1.7192)		
Tar Firm size					-0.1845***		

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					(-6.6675)		
-|AcqQ-TarQ| × Tar Tangibility						0.7208**	
						(2.1325)	
Tar Tangibility						-0.0624	
						(-0.3999)	
-|AcqQ-TarQ| × Tar Abnormal accrual							-0.0060*
							(-1.7677)
Tar Abnormal accrual							-0.0038
							(-1.3438)
-|AcqQ-TarQ| × Same industry	0.2101	0.2222	0.1839	0.2371	0.2268	0.2206	0.2420
	(1.3665)	(1.4576)	(1.1942)	(1.5423)	(1.4877)	(1.4527)	(1.5846)
Same industry	0.3014***	0.3101***	0.3013***	0.3164***	0.3083***	0.3246***	0.3119***
	(3.7307)	(3.8747)	(3.7409)	(3.9361)	(3.8549)	(4.0459)	(3.8636)
-|AcqQ-TarQ| × Acq-tar distance	-0.0068	-0.0091	-0.0081	-0.0070	-0.0043	-0.0087	-0.0053
	(-0.1710)	(-0.2337)	(-0.2012)	(-0.1784)	(-0.1098)	(-0.2209)	(-0.1330)
Acq-tar distance	-0.2370***	-0.2387***	-0.2365***	-0.2378***	-0.2371***	-0.2401***	-0.2377***
	(-9.2712)	(-9.4327)	(-9.1922)	(-9.3603)	(-9.3644)	(-9.4485)	(-9.2931)
Constant	0.8151***	0.3733	0.9392***	0.5654**	0.5287**	0.6952***	0.7720***
	(3.4797)	(1.3201)	(2.9776)	(2.3812)	(2.1952)	(3.0255)	(3.3011)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0966	0.0960	0.0949	0.0952	0.0953	0.0960	0.0950
N	9,931	9,931	9,846	9,931	9,931	9,931	9,747