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Three Essays on Corporate Finance

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Three Essays on Corporate Finance

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Dedicated to my parents Shudian Jing and Chun Yan.

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Three Essays on Corporate Finance

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Chapter 1 hypothesizes that some banks specialize in providing monitoring capital, which includes monitoring services in addition to financial capital, and that such specialization leads them to focus their lending on financially weak firms. I test this hypothesis by constructing a variety of novel measures of banks' monitoring skills and find that financially weak firms are more likely to match with banks that have high monitoring skills and that shocks to firms' financial strength cause them to switch to banks that are a better fit to their new monitoring needs.

Chapter 2 investigates how the switching cost, as a result of informational frictions, affects firms' migration behavior. I propose a novel mechanism whereby banks can coordinate with other institutions with which they conduct business; when a relationship bank determines that its firm matching is inefficient, under some conditions, it can transfer the firm to the bank's partner. Using the loan spread residual as a proxy for unobservable credit shocks, I find consistent evidence that a firm with a larger magnitude residual has a higher likelihood of going to a bank that is not a relationship bank but rather a syndicate partner of its relationship bank; and when the spread residual is positively large, the bank partner to which the firm switches tends to put a high stake in the syndicate, which is consistent with its monitoring role for a distressed firm.

Chapter 3 proposes that alliances are a channel for merger propagation when partnering firms have complementary resources. I confirm the mechanism's main prediction using US data on corporate alliances and merger activity: The likelihood that a firm will be involved in mergers and acquisition (M&A) increases significantly if its partners have also engaged in M&A during the previous two years. My empirical result is not explained by industry-wide M&A activity or company characteristics. I present three additional empirical results: (i) The propagation effect is stronger when I include proxies for the strength of post-partner-merger resource reallocation, which is consistent with the mechanism, (ii) merger propagation effects are not merely localized but rather diffuse through the alliance network, and (iii) partner mergers also lead to a higher likelihood of entering new alliances.

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Chapter 1

Financial Strength and Monitoring Capital

1.1 Introduction

Bank capital can play multiple roles. For example, Holmstrom and Tirole (1997) differentiate between "normal capital," whose value comes only from the provision of funds, and "monitoring capital," whose value also arises from monitoring firms and raising their pledgeable income. Given that the private loan market is the predominant source of external financing for corporations (e.g., Gorton and Winton, 2003), it is important to understand how the different roles of bank capital affect a firm's borrowing behavior.

In this paper, I define monitoring as any activity in which a financial intermediary can engage to improve a firm's financing condition and address the question of how a bank and a firm are matched in the private loan market as a function of their fundamental characteristics. First, I characterize firms by their different "financial strength," which I proxy by using observable measures of credit quality. Second, I differentiate banks by their monitoring skills, which I infer from their historical monitoring-related activities: monitoring intensity (skin in the game), technical skills (covenant intensity), and comparative advantage (industry specialization, focus on distressed firms, and geographic advantage). Given these characterizations of firms and banks, I empirically examine how these two parties are matched.

My paper follows the spirit of much of the research on capital structure. In the same way that financial economists have been studying which trade-offs lead firms to prefer debt versus equity, or private loans versus public bonds, I ask which firms prefer "monitoring banks" versus "normal banks." Specifically, since Jensen and Meckling (1976), debt has been viewed as a mechanism to discipline firms and improve their ability to raise external financing.[1] Likewise, within debt, private

[1]Follow-up work can be seen in Grossman and Hart (1982) and Myers and Majluf (1984), for

loans have been claimed to have a greater ability to govern firms than public bonds do (e.g., Chemmanur and Fulghieri, 1994; Bharath, 2002; Denis and Mihov, 2003). In my paper, I further the understanding of firm capital structure by segmenting the private loan market and investigating whether banks possess different levels of monitoring skills and how this affects which firms they are matched with.

I characterize firms by their financial strength. Specifically, a firm's financial strength can be defined by the maximum amount of its pledgeable income from investments; thus, it depends on a firm's investment opportunities and any financing friction that may result in conflicts of interest between investors and the firm. As far as private loans in this paper are concerned, financial strength refers to a firm's credit quality, which is the determinant of its borrowing capacity from banks.

I assume that banks differ in their monitoring skills, which are defined in this paper as their ability to enhance a firm's pledgeability and hence improve its financing condition. This general notion of monitoring is in fact consistent with extensive studies on how banks can serve firms: as delegated monitors (e.g., Townsend, 1979; Diamond, 1984), information producers (e.g., Brealey, Leland, and Pyle, 1977, Boyd and Prescott, 1986), liquidity providers (e.g., Gorton and Pennacchi, 1990; Holmstrom and Tirole, 1998), and commitment mechanisms (e.g., Calomiris and Kahn, 1991; Diamond and Rajan, 2001). Although each mechanism is different, the ultimate outcome is fundamentally the same in that the mechanism enables the bank to improve a firm's financing condition by reducing one type of financing friction. The concept of monitoring applied in this paper is thus not limited to reducing moral hazard, as is usually the case for the narrow notion of monitoring, but may also include mitigating contracting frictions, improving coordination, and even possibly advising investments. In reality, monitoring may be reflected in banks' practice of writing customized contracts (e.g., line of credit, covenants), regularly keeping firms in check (before default), and verifying information and renegotiating contracts (after default).

To illustrate the implication, one can apply a simple dichotomy and categorize banks into two types: normal banks, which mainly provide monetary capital to firms, and monitoring banks, which also have monitoring technology and thus

example.

provide monitoring capital. Similarly, suppose we have two types of firms: financially weak firms, which have low pledgeable income, and financially strong firms, which have high pledgeable income. I follow Holmstrom and Tirole (1997) and argue that because monitoring capital is more costly, firms always prefer normal capital, which is cheaper, and resort to monitoring capital only if they must. It follows that in a market in which firm financial strength is observable, financially weak firms cannot secure financing from normal banks and must turn to monitoring banks for monitoring service to improve their pledgeable income. Therefore, I should observe symmetric and efficient matching between banks and firms in terms of type. That is, financially strong firms are matched with normal banks while financially weak firms are matched with monitoring banks.

Although Holmstrom and Tirole's (1997) theory seems persuasive, it is not obvious that the private loan market would follow such model. In fact, most prior literature treats banks as homogeneous, and if monitoring skills are not significantly heterogeneous among banks, then banks and firms will simply be matched randomly. Second, if banks do differ in their monitoring skills, it does not have to be the case that highly skilled banks match with firms that have low credit quality, as Holmstrom and Tirole (1997) imply. For instance, Fernando et al. (2005) also propose that underwriter ability and issuer quality can be complementary and thus their matching may be positive assortative,[2] in which case we will observe that monitoring banks are matched with financially strong firms.

I test the hypothesis empirically with U.S. private loans. As banks' monitoring fundamentals are hardly measurable to an econometrician, I apply a variety of proxies and verify results' consistency. Specifically, to measure a bank's frequency of monitoring, I compute its historical skin in the game based on the average percentage share of its past syndicated loans, following the argument that monitoring requires a higher stake from the agent to commit to an appropriate incentive (e.g., Khorana, Servaes, and Wedge, 2007; Demiroglu and James, 2012; Chemla and Hennessy, 2014). Second, covenants are indispensable tools that banks use to perform the monitoring (e.g., Sufi, 2009; Roberts and Sufi, 2009; Nini, Smith, and Sufi, 2009). To capture the frequency of a bank's use of heavily covenant-based contracts,

[2]Studies that find evidence for positive assortative matching in other settings can be seen in, for example, Sørensen (2007) for the venture capital market and Custodio and Metzger (2013) for the market for financial expertise.

I construct a bank's covenant intensity using its average covenant strictness on its previous contracts signed, where I follow Murfin (2012) to compute a loan contract's covenant strictness. Next, monitoring characteristics can be firm-specific as well. In particular, some banks may specialize in monitoring one type of firm and have little monitoring advantage for others. Therefore, I quantify a bank's specialization in monitoring a specific industry by its past percentage allocation of capital invested in firms in that industry. Similarly, I construct distress specialization based on a bank's past percentage allocation invested in financially distressed firms. Last, I measure a bank's geographic advantage to a firm by whether the bank is located close to the firm. Of all five proxies, the first mainly concerns a bank's general monitoring skills, while each of the rest captures one dimension of a bank's monitoring specialization.

The ideal indicator of a security's underlying quality is its market price if it is traded publicly. Therefore, I use the variables that are closest to the hypothetical market price of a private loan—credit rating and loan spread—and check robustness across other measures, including such default predictors as Altman's Z score (Altman, 1968) and Ohlson's O score (Ohlson, 1980), such financial distress indices as the WW (Whited and Wu, 2006) index and the SA (Hadlock and Pierce, 2010) index, the KMV-Merton model implied rating (Duan, Gauthier, and Simonato, 2005), and the first component of their principal-component decomposition.

I find that firms with low credit ratings and high loan spreads are more likely to be matched with banks with high-level monitoring skills, namely, high historical skin, covenant intensity, industry specialization, and distress specialization, as well as close proximity to the firm. These results are robust across specifications and to inclusion of general firm-level and bank-level characteristics. In particular, the literature on bank heterogeneity has shown that large banks tend to lend to large firms while small banks tend to finance small firms (e.g., Berger and Udell, 1995; Berger, Klapper, and Udell, 2001; DeYoung, Hunter, and Udell, 2004). The mechanism proposed can potentially explain this pattern; this notwithstanding, the robust results after controlling for size suggest that the mechanism can also explain firm-bank matching beyond the size fact. Furthermore, I find that firms receiving shocks to their financial strength are more likely to switch to new banks; the type of bank to which they switch is also consistent with the type of shock: A negative shock makes a firm switch to a monitoring bank.

This paper is mainly related to two strands of literature. First, the study of separating normal capital from monitoring capital in the private loan market contributes to the literature on capital structure (e.g., Titman and Wessels, 1988; Hovakimian, Opler, and Titman, 2001). Second, it investigates firm-bank matching according to banks' monitoring skills and firms' financial strength, complementing the finance literature regarding the implications of bank heterogeneity for firm borrowing (e.g., Mian, 2006; Ross, 2010).

The remainder of the chapter is organized as follows. Section 1.2 elaborates upon my fundamental idea and develops the hypothesis. Section 2.3 describes the data and explains the sample and variable construction, and Section 2.4 presents the corresponding results. Finally, Section 1.5 discusses further insights from the proposed mechanism, with concluding remarks in Section 3.5.

1.2 Hypothesis Development

Private loans, as the predominant source of external financing, allow borrowers and lenders to sign a specified financing contract with a level of customization that cannot be achieved by standardized public capital markets. Detailed information about the firm's financial condition is incorporated into the loan contract, where the included specific terms work as effective mechanisms to discipline the borrower and improve the borrower's pledgeable income. Extensive research has focused on investigating the borrower's financial characteristics by relating them to the contract terms of loans, but few studies have devoted attention to the lender's side. On top of firm characteristics, I aim to add bank fundamentals and investigate how different banks affect firms' borrowing behavior in the private loan market.

First, I assume that firms that participate in the loan market differ in their fundamentals of financial health, which drive their ability to issue private loans. Firm financial strength can be quantified by the amount of income that can be pledged from the firm's investment; put simply, firm financial strength indicates the maximum amount of money that can be raised against its investment. Therefore, it is a function of a firm's real side and any financing friction that could result in conflicts of interest between investors and the firm.

Second, I assume that banks, as suppliers of capital, also differ in their monitoring skills. The notion of monitoring skills used in this paper is broadened to include any skill that can improve firms' financing conditions (i.e., pledgeable income) for firms in need. Specifically, it may include the ability to reduce the moral hazard of firms, mitigate contracting frictions by writing a more complete contract, coordinate with other major investors, and even possibly advise investments. In reality, it may be reflected in the bank practice of writing customized contracts (e.g., line of credit, covenants), regularly keeping firms in check (before default), and verifying information and renegotiating terms (after default). Furthermore, the monitoring skills here can also include screening skills, which are discussed at greater length in Section 1.5.

To illustrate my idea more effectively, apply a simple dichotomy and classify banks into normal banks—those that have no or low monitoring skills and see their only function as providing funds to firms—and monitoring banks—those that can provide monitoring capital, which consists of not only monetary capital but also add-on services deriving from their monitoring skills. Similarly, suppose we have two types of firms: financially weak firms—those that have low pledgeable income—and financially strong firms—those that have high pledgeable income.

After characterizing firms and banks in this way,[3] I examine the simple research question of how different bank capital is allocated to corporations by looking at how heterogenous banks and firms are matched in the private loan market. Put simply, do financially weak firms value bank skills more than financially strong firms do, or is the opposite true? I follow Holmstrom and Tirole (1997) and argue that, assuming that monitoring capital is more costly, firms always prefer normal capital, which is cheaper, and resort to expensive capital only if they must.

It follows that, in an economy with no information asymmetry, financially weak firms cannot obtain financing from normal banks and must turn to monitoring banks for additional service that improves their pledgeable income. If monitoring skills were costly for banks to acquire ex-ante, those with monitoring skills would also strictly prefer to finance financially weak firms to make these skills worth their costs.[4] Therefore, the implication is symmetric and efficient matching between banks

[3] This characterization is consistent with the way in which Holmstrom and Tirole (1997) characterize firms and capital.

[4] Ex-ante costly acquisition of skills is not the only possible reason why monitoring banks may strictly prefer lending to financially weak firms; if monitoring banks could get some economic rents

and firms according to their types.[5] Specifically, financially strong firms are matched with normal banks while financially weak firms are matched with monitoring banks.

1.3 Data and Variable Construction

1.3.1 Data

I test the hypothesis above using the LPC DealScan bank loans dataset in which I can identify borrower-lender pairs and loan terms. I extract all U.S. loans from 1988 through 2006 and drop loans whose starting date, duration, and spread are unknown. I trace each bank's and company's ultimate parent if that information is available. I focus on the heterogeneity of lead banks, which are more active players in originating loans than participating banks and therefore should better fit the monitoring role proposed in the story. In fact, as documented in the literature (e.g., Rhodes, Clark, and Campbell, 2004), participating banks usually play a passive role in investing and communicating with firms. Following Bharath et al. (2007) and Gatev and Strahan (2009), I define a bank as a participant if the term *participant* appears in the role of the lender and as a lead bank otherwise. In non-syndicated loans, the only bank will be defined as the lead bank regardless of its role.

Following Campello et al. (2011), I also construct such loan characteristics as loan size, maturity dummies, performance pricing indicator, loan purpose, and loan type dummies, supplemented with monthly market credit spread and term spread; detailed definitions for these variables are listed in Table 3.1. Furthermore, I use the linking table provided by Chava and Roberts (2008) to match with borrowers' financial information in Compustat. Constructed firm-level controls include leverage, market-to-book ratio, profitability, size, tangibility, and research and development (R&D); seeTable 3.1 for detailed definitions.

I also manually match banks from DealScan to the Bank Regulatory Database from the Wharton Research Data Service (WRDS). Specifically, I use a text-matching

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ex-post from financing financially weak firms, they would also strictly prefer lending to financially weak firms.

[5]If monitoring banks do not a have strict preference for financially weak firms, we may have asymmetric matching: monitoring banks finance financially weak firms as well as financially strong firms. This may well occur, but I believe symmetric matching is a more natural conjecture to test.

algorithm to perform a mechanical matching based on name, state, zip code, and the implied operation window from loans data, and then check each match manually. I then hand match the remaining banks by name. When it comes to multiple candidates for matches (i.e., those with identical names), I check state, zip code, and the operation window to pin down the exact match. I match names at both the parent level and the subsidiary level. For parents, I start with the bank holding company database and try the commercial bank database if I cannot find the parent, and vice versa for subsidiaries. I have successful matches for 477 parents and 852 subsidiaries. Given that this matching process often involves discretion, I use these data only if they are necessary to construct my main variables of interest or to control for potential endogeneity problems.

1.3.2 Firm Financial Strength

The firm and bank characteristics in which I am interested (i.e., firm financial strength and bank monitoring skills) are fundamental variables and thus hardly measurable, even if assumed to be observable in the story. Therefore, the methodology employed in this paper is to use observables that are functions of those fundamental variables as proxies. By definition, these variables must be endogenous and dependent on firm or bank fundamentals so that I can rely on their endogenous variations to mirror the exogenous variations in the fundamentals. These economic endogenous variables do not necessarily imply an endogeneity problem in econometrics. However, the study will be subject to endogeneity if there are measurement errors, which can be twofold: (1) the proxy is coarse with noise and this results in an attenuation problem and (2) it captures a different fundamental and thus corresponds to an alternative story. To overcome such possible mismeasurement, my method is to adopt a variety of proxies for both firm financial strength and bank monitoring skills and verify robustness across these proxies. Nevertheless, each proxy is still subject to attenuation errors, which work against me, and therefore the true magnitudes can be highly underestimated if the precision of proxies is relatively low.

If bank loans were publicly traded, the ideal measure for the underlying quality of a firm's loan would be its market price. Thus, the closer the proxies are to the hypothetical market price, the better they are. The first measure I adopt is credit rating, which is a publicly available composite measure of the firm's credit quality to banks. I transform credit rating, a multi-category variable, into a dummy—*junk*—equal to 1 if the firm has an S&P rating lower than BB and 0 otherwise. The advantage of this measure is its simplicity as well as its wide use by market participants. The second proxy is *loan spread*, namely, the interest rate charged on the loan subtracting off the London interbank offered rate (LIBOR). As compared to credit rating, loan spread is a more precise measure, not only from its continuity but also from the fact that it is indeed the actual price the bank in question requires the firm to pay.[6] I also check robustness using such default predictors as Altman's Z score (Altman, 1968) and Ohlson's O score (Ohlson, 1980), such financial distress indices as the WW (Whited and Wu, 2006) index and the SA (Hadlock and Pierce, 2010) index, KMV model implied rating, and the first component of their principal-component decomposition. For brevity, I present tests using junk and loan spread only, but other proxies yield qualitatively similar results.

Table 1.1 presents conditional means of firm-level characteristics and common financial health measures sorted on junk and loan spread at the loan level. Panel A shows the conditional means of the characteristics as a function of junk, and Panel B shows conditional means sorted on loan spread divided into quintiles, with one being the lowest. Both panels show that firms with lower credit ratings or higher loan spreads are usually smaller, have worse investment opportunities, and are more levered.[7] This is consistent with our priors on the relationships between a firm's financial health and its general characteristics. The bottom half of each panel shows that junk or loan spread has a consistent relationship with other common measures of firm financial health. From Table 1.1, one can see that junk and loan spread are reasonably valid indicators of a firm's credit quality.

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[6]Though the loan spread and the matching may be determined simultaneously, based on rational expectation, the ex-post loan spread is an unbiased measure for ex-ante firm financial strength; the loan spread may also capture private information on firm financial strength but that should be orthogonal to publicly observable financial strength ex-ante. I have also tried the fitted value of loan spread from a spread-predicting regression and all my results are robust with this measure as well.

[7]In an extended table with more firm characteristics, firms with low credit rating and high spreads are also shown to have more tangible assets and R&D expenditures.

Table 1.1: Firm Characteristics and Financial Health vs. Junk and Loan Spread.

The table presents conditional means of firm level characteristics and common financial health measures sorted on junk and loan spread at the loan level. Junk is a dummy indicating a firm with S&P rating lower than BB and loan spread is the natural logarithm of the amount the borrower pays in basis points over LIBOR for each dollar drawn down including any annual (or facility) fee paid to the bank group. Panel A shows conditional means of the characteristics on junk. Panel B shows conditional means of the characteristics sorted on loan spread divided into quintiles with one being the lowest. The last column of each panel computes the difference of the top quantile and bottom quantile. Size is the natural logarithm of the total sales of the borrower, M/B is the market-to-book ratio and leverage is the book leverage. Negative Z Score is minus Altman's Z score.

Panel A: Sorting on Junk

junk	0	1	(1-0)
size	8.54	6.74	-1.80***
M/B	1.83	1.46	-0.37***
leverage	0.44	0.59	0.15***
tangibility	0.36	0.34	0.02***
loan spread	4.06	5.33	1.27***
negative Z Score	-2.00	-1.38	0.62***
O Score	-1.49	-0.19	1.30***
WW Index	-4.30	-0.31	3.99***
SA Index	-3.82	-3.45	0.37***
KMV rating	0.13	0.32	0.19***

Panel B: Sorting on Spread

loan spread	1	2	3	4	5	(5-1)
size	8.26	6.77	6.06	5.67	5.20	-3.06***
M/B	2.10	1.84	1.74	1.66	1.59	-0.51***
leverage	0.37	0.36	0.41	0.42	0.46	0.09***
tangibility	0.34	0.33	0.31	0.30	0.29	0.05***
junk	0.03	0.31	0.73	0.75	0.82	0.79***
negative Z Score	-2.18	-2.17	-1.91	-1.69	-1.04	1.14***
O Score	-1.77	-1.41	-0.98	-0.51	0.29	2.06***
WW Index	-0.42	-0.33	-0.29	-0.26	-0.24	0.18***
SA Index	-3.77	-3.44	-3.24	-3.10	-2.97	0.80***
KMV rating	0.08	0.12	0.19	0.28	0.38	0.30***

1.3.3 Bank Monitoring

The inability to observe bank-specific activities makes the task of measuring monitoring skills challenging. I have constructed five measures to capture banks' monitoring ability. First, agents use skills in which they specialize, and thus banks that exhibit high frequency of monitoring their portfolio firms should possess high levels of monitoring skills. Also, monitoring takes a bank effort, time, and resources and therefore should be motivated appropriately to occur. Following the literature on moral hazard (e.g., Khorana, Servaes, and Wedge, 2007; Demiroglu and James, 2012; Chemla and Hennessy, 2014), I argue that, for incentive purposes, monitoring banks are expected to put considerable skin in the game. It then follows that banks that often have high stakes in loans are likely to be banks that have high frequency of engaging in monitoring activities. I interpret the skin in the game as a bank-level characteristic and use it to describe a bank's monitoring frequency. Specifically, I construct the variable, *historical skin*, by the average percentage share of the bank's loans syndicated over the past five years.[8] For example, if a bank had syndicated three loans over the past five years, in which it accounted for 40%, 50%, and 60% of the capital needed, respectively, then its historical skin as of today would be 50%.

Similarly, I construct a variable that captures the frequency of a bank writing a more covenant-based contract. Contract covenants work as very important tools for bank creditors' use in monitoring a firm's activities (e.g., Sufi, 2009; Roberts and Sufi, 2009; Nini, Smith, and Sufi, 2009). Covenants can be related to the concept of monitoring applied in this paper via three specific aspects. First, a bank's writing a more complex contract indicates its ability to write a more complete contract and thus its ability to reduce potential contracting frictions. Second, after a more covenant-based contract is signed, the bank has to keep an eye on the firm and regularly keep it in check. Third, a stricter contract means a higher probability of contract violation, in which case the bank must step in, secure more control over the firm, and make critical decisions. Specifically, I build a variable called *covenant intensity*, defined by the average covenant strictness of all loan contracts signed over the past five years. For covenant strictness on the contract level, I follow

[8] Around 60% of the data on bank shares are missing, but Ivashina (2009) reviews Securities and Exchange Commissions reports for random companies and does not find systematic bias in the characteristics of companies that disclose that information.

Murfin (2012) and build a composite measure to indicate the strictness of covenants used in each contract,[9] which captures the following information: (1) the number of covenants: the more covenants involved in a contract, the stricter the contract is, (2) the slackness of covenants: a covenant far from being violated has different effects on a firm than one that is close to binding, and (3) the covariance between covenants: two covenants with very positively correlated probability of breaking the thresholds are not as strict as two covenants that rely on two independent financial variables.

Monitoring ability can depend on a firm's characteristics as well. Some banks can be experts in monitoring any firm unconditionally, as historical skin attempts to capture, while other banks may be only advantaged in monitoring firms of a particular type. Specifically, a bank can have comparative advantages in monitoring firms that come from a specific industry; for example, a bank can be more specialized in monitoring bio-tech companies while being less efficient in dealing with the food industry. I attempt to capture such industry specialization through a bank's percentage of capital that is allocated to firms of the same Standard Industrial Classification 3 (SIC3), against all loans originated over the past five years.[10] For example, a bank that had invested $1 billion in all its loans over the past five years, half of which was assigned to bio-tech firms, then has a monitoring specialization in the bio-tech industry of 0.5. Likewise, I construct *distress specialization* by the percentage of the bank's capital allocated to financially distressed firms over the course of the past five years; financially distressed firms are defined as firms that belong to the top quintile of the industry-year adjusted WW Index.[11]

Finally, a bank can have geographic advantages in monitoring a firm to which it is physically close, to the extent that physical distance matters in the bank's ability to check on the firm and/or the advantage of acquiring the firm's information pertinent to monitoring. I measure the distance in miles between the bank and the firm using information on zip code, city (if other data are not available), and state (if other data are not available). Both DealScan and Bank Regulatory have relevant but incomplete information and, to minimize the effect of possible erroneous

[9]Refer to Murfin (2012) for details on the computation of the variable.

[10]I also compute a variant of it by frequency of investing in the corresponding industry instead of by dollar terms, and results are qualitatively similar.

[11]I also compute a variant of it not by dollars but by frequency of investing in financially distressed firms and/or by changing from WW into SA index, and the results are qualitatively similar.

matching on the accuracy of location, I use location information from DealScan first and complement it with Bank Regulatory data. Moreover, I compute distance using the location of the bank subsidiary and turn to the bank parent if the location information for the subsidiary is not available. To deal with the concern that the geographic advantage for a bank of a firm is not linear in distance and in fact is more likely to exist only within a degree of distance, I follow Sufi (2007) and transform the continuous distance into a dummy indicating whether the bank is local to the firm. Specifically, I use the cutoff of 34 miles, the 10th percentile of my sample, to define whether a bank is local.[12]

While all financial strength proxies try to measure one fundamental, the proxies for bank monitoring characteristics exhibit some diversity. Except for the first proxy, historical skin, which aims to measure a bank's general monitoring skills, each of the other four attempts to capture one dimension of a bank's monitoring specialization. With that being said, if the bank fundamental of interest (i.e., the level of monitoring skills) were directly observable, it should be characterized by several factors instead of a single variable because one bank's monitoring skills can vary for different firms.

The summary statistics of bank characteristics are presented in Panel A of Table 3.1. The top half presents general bank characteristics whose summary statistics are similar to those in other papers that study banks. The bottom half presents monitoring characteristics that I construct. The strong autocorrelations show persistence of these monitoring characteristics and indicate that these measures are stable bank-level variables and reflect bank fundamentals that we do not expect to vary dramatically over time. The summary statistics of the sample loans are presented in Panel B of Table 3.1, with bank monitoring variables averaged at the loan level. The final sample of loans has around 20,000 observations whose summary statistics are very similar to those in other papers that study bank loans using the same database. However, due to limited availability of credit rating, its sample includes less than 10,000 observations. To be conservative, I work with this sample instead of a much larger sample in which missing values are replaced with 1 because then financially weak firms would be dominated by firms that do not have credit ratings.

[12]Results are also robust to to other similar cutoffs or a dummy indicating whether the bank and the firm belong to a zip code with the same first three digits.

Table 1.2: Summary Statistics.

The table presents means, standard deviations, percentiles, and the number of observations for each variable at the loan level. Size is the natural logarithm of the total sales of the borrower. Leverage is the book leverage and M/B is the market-to-book ratio. R&D is R&D expenditures normalized by its total assets with missing values replaced by zeros. Tangibility is the borrower's property, plant and equipment divided by total assets. Junk is a dummy indicating a firm with S&P rating lower than BB. No. of banks is the number of banks forming the syndicate of the loan and no. of lead banks is the number of lead banks in the syndicate. Loan size is the natural logarithm of the amount of money borrowed. Maturity shows the extension of the loan, in number of months, from signing date to expiration date. Loan spread is the natural logarithm of the amount the borrower pays in basis points over LIBOR for each dollar drawn down including any annual (or facility) fee paid to the bank group. Historical skin is the average allocation in percentage the bank invests in all its syndicates of the past five years and averaged at the syndicate level. Covenant intensity is a bank's average covenant strictness on its previous contracts signed, where I follow Murfin (2012) to compute a loan contract's covenant strictness. Industry specialization is the bank's capital in percentage in the portfolio of loans originated over the past five years which is allocated to firms of the same SIC3 to the firm of interest. Distress specialization is the bank's capital in percentage in the portfolio of loans originated over the past five years which is allocated to financially distressed firms, which are defined as firms of the top quintile of industry-year adjusted WW Index. Both specialization measures are averaged at the loan level. Local bank is the proportion of banks which are within 34 miles of the firm in distance.

Panel A: Banks

	Autocorrelation	mean	sd	p5	p50	p95
bank size	N.A.	16.05	1.94	12.59	1.19	19.09
loan/asset	N.A.	0.61	0.14	0.33	0.64	0.79
bank profitability	N.A.	0.011	0.004	0.003	0.011	0.017
bank tier 1 cap./asset	N.A.	0.075	0.016	0.055	0.072	0.010
historical skin	0.94	0.50	0.39	0.00	0.57	1.00
industry spec.(top)	0.95	0.54	0.41	0.00	0.53	1.00
distress spec.	0.93	0.01	0.23	0.00	0.00	0.76
covenant intensity	0.90	0.29	0.31	0.00	0.22	0.82
No. of obs.	796					

Panel B: Loans

	N	mean	sd	p5	p50	p95
size	20230	6.43	1.94	3.32	6.39	9.74
leverage	20230	0.41	0.24	0.00	0.41	0.82
M/B	20230	1.79	1.21	0.87	1.45	3.88
R&D	20230	0.03	0.12	0.00	0.00	0.13
tangibility	20230	0.32	0.23	0.04	0.26	0.80
junk	9104	0.41	N.A.	N.A.	N.A.	N.A.
no. of banks	20230	7.18	7.89	1.00	5.00	22.00
no. of lead banks	20230	3.18	3.43	1.00	2.00	10.00
loan size	20230	4.51	1.74	1.39	4.61	7.13
maturity	20230	44.71	24.48	12.00	48.00	84.00
loan spread	20230	4.91	0.87	3.22	5.16	6.00
historical skin	20230	0.49	0.17	0.24	0.48	0.75
covenant intensity	20230	0.33	0.20	0.00	0.41	0.61
industry specialization	20230	0.03	0.08	0.00	0.01	0.12
distress specialization	20230	0.04	0.07	0.01	0.02	0.12
local bank	20230	0.08	0.24	0.00	0.00	1.00

1.4 Results

1.4.1 Unilateral Matching

How do firms of different credit quality select banks with different monitoring skills? To obtain some rough answers to this question, first, I perform a simple conditional mean test comparing the average monitoring skills across different groups of firms sorted by financial strength variables, namely, junk and loan spread. Table 1.3 presents the results, with junk shown in Panel A and loan spread in Panel B, and the last column in each panel shows the mean differences between the highest and lowest quintiles. We can see from both panels that as junk or spread increases, the matched banks' historical skin, covenant intensity, industry specialization, and distress specialization increase and distance decreases, and the trends exhibit stable patterns in that as the financial strength of firms changes, the monitoring characteristics of banks change monotonically. These results are consistent with the hypothesis that financially weak firms tend to select banks with high-level monitoring skills.

Another simple way to test the hypothesis is by investigating frequency tables of firm-bank matching. In a simple economy with only two types of banks, monitoring and normal banks, and two types of firms, financially strong and weak firms, we should observe abnormal clustering of financially weak firms and monitoring banks and of financially strong firms and normal banks. Specifically, the frequency of financially weak firms associating with monitoring banks and of financially strong firms associating with normal banks should be significantly higher than random matching would suggest. I therefore follow this logic and construct 2×2 in-sample frequency tables of firm-bank matching based on firm type, proxied by junk and loan spread, and on bank type, proxied by historical skin, industry specialization, distress specialization, and negative distance. Each continuous variable has been transformed into a dummy, with the cutoff being its industry-year adjusted median and with zero meaning below the median. I compare these real frequencies with those implied by the null hypothesis—firm and bank types are randomly paired—and test the significance of their differences. The results are presented in Table 1.4 and Table 1.5, with actual frequency placed on the left, implied frequency from the null hypothesis in the middle, and the difference between the two on the right. Except for industry specialization, all results indicate that highly frequent matching between financially strong and low-monitoring types and between financially weak

Table 1.3: Conditional Mean Tables: Financial Strength vs. Monitoring.

The table presents conditional means of monitoring characteristics at the loan level sorted on the firm financial strength measures, junk and loan spread. The last column of each panel computes the difference between the top and bottom quantiles. Junk is a dummy indicating a firm with S&P rating lower than BB and loan spread is the natural logarithm of the amount the borrower pays in basis points over LIBOR for each dollar drawn down including any annual (or facility) fee paid to the bank group. Historical skin is the average allocation in percentage the bank invests in all its syndicates of the past five years and averaged at the syndicate level. Covenant intensity is a bank's average covenant strictness on its previous contracts signed, where I follow Murfin (2012) to compute a loan contract's covenant strictness. Industry specialization is the bank's capital in percentage in the portfolio of loans originated over the past five years which is allocated to firms of the same SIC3 to the firm of interest. Distress specialization is the bank's capital in percentage in the portfolio of loans originated over the past five years which is allocated to financially distressed firms, which are defined as firms of the top quintile of industry-year adjusted ww Index. Both specialization measures are averaged at the loan level. Distance is the average distance between the firm and syndicate banks.

Panel A: Sorting on Junk

junk	0	1	(1-0)
historical skin	0.404	0.441	0.037***
covenant intensity	0.338	0.371	0.033***
industry specialization	0.023	0.028	0.005***
distress specialization	0.022	0.032	0.010***
distance	7.430	7.239	-0.191***

Panel B: Sorting on Spread

loan spread	1	2	3	4	5	(5-1)
historical skin	0.433	0.464	0.475	0.510	0.560	0.127***
covenant intensity	0.290	0.323	0.345	0.353	0.367	0.077***
industry specialization	0.022	0.024	0.029	0.033	0.046	0.024***
distress specialization	0.024	0.028	0.035	0.041	0.056	0.032***
distance	7.250	7.000	6.870	6.780	6.710	-0.540***

and high-monitoring types suggests a systematic pattern and, therefore, rejects the null hypothesis of random matching.

The inconsistent result associated with industry specialization can be attributed to the primitiveness of the frequency tests. To examine in a more rigorous way how firms select banks with different monitoring skills as a function of firm financial strength, I apply ordinary least squares (OLS) regressions using the sample of loans where the dependent variable is a selected proxy for the monitoring ability of banks and regressed on firm financial strength—junk or loan spread—with general firm characteristics controlled including size, leverage, the market-to-book ratio (M/B), R&D, and tangibility, and with industry and year fixed effects (see the specification below). Monitoring characteristics are averaged at the loan level for syndicated loans.

$$MonitoringSkills = a \times FinancialStrength + controls$$

Note that in the story financial strength—fundamentals on a firm's financial condition with issuing loans—is a sufficient statistic that banks must know to make the loan-granting decision, and all other firm characteristics that are exogenous and publicly available only have influence through financial strength. Therefore, the univariate tests in Table 1.3 stand up to simplicity as well as validity. Ideally, all other controls will contribute nothing to how firm financial strength influences bank selection after the firm financial strength itself has been taken into account. To control for non-financial strength-related effects as well as improve efficiency, I include other firm-level controls.

One can see that, except for local banks, all show significant relationships between the type of bank and the financial strength of the firm: firms with lower credit rating or higher loan spread are associated with banks with high historical skin, covenant intensity, industry specialization, and distress specialization. These results are consistent with the implication from the story that financially weak firms are more likely to select banks with high monitoring skills that can improve their financing conditions and help get them financed. A change in the value of junk explains these bank-level monitoring characteristics ranging from 4% to 16% of their standard deviations; a one standard deviation variation in loan spread explains from 2% to 10% of the standard deviations of those monitoring characteristics. The lack of

Table 1.4: Frequency Table: Qualities vs. Monitoring.

The table presents the in-sample frequency of firm-bank matching as a function of firm qualities, proxied by junk, and bank monitoring skills, proxied by historical skin, industry specialization, distress specialization and negative distance. Each continuous variable is made into dummies with the cutoff determined by its industry-year median with zero being below median. In each panel, the left frequency shows the ACTUAL frequency of financially strong/weak firms matched with high/low-monitoring-skill banks; the middle frequency gives the frequency of financially strong/weak firms matched with high/low-monitoring-skill banks if firms and banks are randomly matched using actual frequency distribution of banks and firms. The right frequency computes the difference of the actual frequency and the frequency under the null hypothesis of random matching.

Panel A: Junk vs. Historical Skin

		historical skin							
		0	1		0	1		0	1
junk	0	40.6	15.3	0	37.6	18.4	0	3.0	-3.0
	1	26.6	17.5	1	29.6	14.5	1	-3.0	3.0

Panel B: Junk vs. Covenant Intensity

		covenant intensity							
		0	1		0	1		0	1
junk	0	27.2	31.5	0	25.8	32.9	0	1.4	-1.4
	1	16.8	24.5	1	18.2	23.1	1	-1.4	1.4

Panel C: Junk vs. Industry Specialization

		industry specialization							
		0	1		0	1		0	1
junk	0	25.4	31.1	0	26.8	29.7	0	-1.4	1.4
	1	22.1	21.5	1	20.6	22.9	1	1.4	-1.4

Panel D: Junk vs. Distress Specialization

		distress specialization							
		0	1		0	1		0	1
junk	0	38.0	20.7	0	34.7	24.1	0	3.4	-3.4
	1	21.0	20.3	1	24.4	16.9	1	-3.4	3.4

Panel E: Junk vs. Negative Distance

		negative distance							
		0	1		0	1		0	1
junk	0	37.8	17.5	0	35.0	20.3	0	2.8	-2.8
	1	25.5	19.2	1	28.3	16.4	1	-2.8	2.8

Table 1.5: Frequency Table: Qualities vs. Monitoring.

The table presents the in-sample frequency of firm-bank matching as a function of firm qualities, proxied by loan spread, and bank monitoring skills, proxied by historical skin, industry specialization, distress specialization and negative distance. Each continuous variable is made into dummies with the cutoff determined by its industry-year median with zero being below median. In each panel, the left frequency shows the ACTUAL frequency of financially strong/weak firms matched with high/low-monitoring-skill banks; the middle frequency gives the frequency of financially strong/weak firms matched with high/low-monitoring-skill banks if firms and banks are randomly matched using actual frequency distribution of banks and firms. The right frequency computes the difference of the actual frequency and the frequency under the null hypothesis of random matching.

Panel A: Spread vs. Historical Skin

		historical skin							
		0	1		0	1		0	1
loan spread	0	31.2	24.0	0	27.6	27.6	0	3.6	-3.6
	1	18.8	26.0	1	22.4	22.4	1	-3.6	3.6

Panel B: Spread vs. Covenant Intensity

		covenant intensity							
		0	1		0	1		0	1
loan spread	0	28.6	26.6	0	27.6	27.6	0	1.0	-1.0
	1	21.4	23.4	1	22.4	22.4	1	-1.0	1.0

Panel C: Spread vs. Industry Specialization

		industry specialization							
		0	1		0	1		0	1
loan spread	0	27.2	27.9	0	27.6	27.6	0	-0.4	0.4
	1	22.8	22.1	1	22.4	22.4	1	0.4	-0.4

Panel D: Spread vs. Distress Specialization

		distress specialization							
		0	1		0	1		0	1
loan spread	0	30.9	24.3	0	27.9	27.3	0	3.0	-3.0
	1	19.6	25.2	1	22.6	22.2	1	-3.0	3.0

Panel E: Spread vs. Negative Distance

		negative distance							
		0	1		0	1		0	1
loan spread	0	28.0	23.0	0	25.5	25.5	0	2.5	-2.5
	1	22.1	27.0	1	24.5	24.5	1	-2.5	2.5

strong economic significance mainly comes from the lack of precision in those proxies based on three aspects. First, those measures are only proxies for the unobservable fundamentals and therefore produce attenuation errors. Second, each proxy for bank monitoring characteristics only captures one dimension of a bank's monitoring specialization, and thus the inference of the relationship between a firm's credit quality and a bank's monitoring skills from looking at only one monitoring factor unquestionably underestimates the true relationship. Last, for a syndicated loan, not all lead banks are necessarily monitoring banks that grant loans to financially weak firms. Thus, the average monitoring characteristic of all syndicate banks used in the test may include considerable noise. The empirical approach adopted in this paper is more appropriate to address the research question qualitatively than quantitatively.

The number of analysts covering the stock is controlled for the possibility there may exist different monitoring difficulties across firms that are not just a function of financial strength. The result shows almost none relationship between the analyst coverage and the firm's choice of its bank capital. That is not surprising as that should mainly proxy for the level of firm information asymmetry which is an argument of financial strength. Therefore, after my financial strength variable is put in place, the number of analysts covering the stock should provide no additional explanatory power, as born out in the data.

For local banks, I present the regression results, one with size of firm controlled and one without. Interestingly, results can differ greatly depending on whether size is included as a regressor or not. Specifically, in Panel B, loan spread strongly predicts the distance between the bank and the firm but shows no relationship at all after the size is controlled. In all other tests, I have tried with different proxies for financial strength, such as Z score, O score, WW index, and SA index, and for geographic advantage such as local with different cutoffs, distance, dummy of the same zip code, dummy of the same state, and dummy of the same country, and this pattern still holds. That is, the coefficient is always positively significant when firm size is not controlled while I find unstable results, sometimes significant, sometimes not, when size is controlled. The possible reasons are: firm size might capture all information related to geographic advantage, banks may not rely on geographic convenience to monitor firms, or distance might capture the size effect.

Furthermore, I intentionally use firm size as a control for another specific purpose. The literature documents that big banks tend to finance big firms while small banks lend to small firms. Suppose the matching mechanism I propose simply proxies for matching by size; that is, my firm financial strength variable is simply a proxy for firm size, while my bank skill variable proxies for bank size. If so, then firm size, itself the most precise measure of firm size, will capture all the effect and leave my financial strength proxy insignificant. However, if my mechanism has its own validity, then the corresponding coefficient should still be significant, even after the addition of firm size, as seen in both panels. In fact, some of the coefficients of size in Panel A are not significant, which might suggest that size can proxy for firm financial strength to some extent and, hence, after firm financial strength itself is controlled, size is no longer influential.

1.4.2 Bilateral Matching

Now I implement a bilateral matching test, by which I attempt to examine which combination of firm financial strength and bank monitoring skills is more likely to lead to a successful matching. The term *bilateral* here means that both firms and banks are active in searching for optimal counterparts based on their exogenous characteristics. The advantage of a bilateral analysis is that it allows for controlling for both bank and firm characteristics, while in the unilateral regressions above, only firm characteristics can be controlled.

Only successful pairs of banks and firms are observed, and to make up for unsuccessful firm-bank pairs, I apply the common practice in the literature of bilateral matching (e.g., Sufi, 2007; Lindsey, 2008) and construct the sample by making all possible firm-bank pairs from banks and firms that participated in that year of the loan market. I perform a linear probability regression in which the dummy indicating successful matching is regressed on the firm financial strength variable, bank monitoring variable, and most importantly their interaction, with general firm and bank characteristics such as firm size, firm M/B, firm leverage, bank size, bank loan ratio, bank profitability, and bank holding company dummy and year and industry fixed effects controlled[13], as shown in the following specification. Given that my firm proxies are inversely related to financial strength, I should expect a to be positive. As junk and loan spread essentially proxy for one fundamental, as I do

[13]Results are robust to inclusion of additional firm characteristics, such as tangibility and R&D, and bank characteristics, including deposits ratio and tier 1 capital ratio.

Table 1.6: Unilateral Matching.

This table shows the OLS regression of the sample of loans examining what type of firms are matched with banks with high level monitoring skills. The dependent variable in each column is a proxy for bank monitoring skill at the loan level and the main independent variable is borrower financial strength proxies junk in Panel A and loan spread in Panel B with firm level controls. Junk is a dummy indicating a firm with S&P rating lower than BB and loan spread is the natural logarithm of the amount the borrower pays in basis points over LIBOR for each dollar drawn down including any annual (or facility) fee paid to the bank group. Historical skin is the average allocation in percentage the bank invests in all its syndicates of the past five years and averaged at the syndicate level. Covenant intensity is a bank's average covenant strictness on its previous contracts signed, where I follow Murfin (2012) to compute a loan contract's covenant strictness. Industry specialization is the bank's capital in percentage in the portfolio of loans originated over the past five years which is allocated to firms of the same SIC3 to the firm of interest. Distress specialization is the bank's capital in percentage in the portfolio of loans originated over the past five years which is allocated to financially distressed firms, which are defined as firms of the top quintile of industry-year adjusted ww Index. Both specialization measures are averaged at the loan level. Local bank is the proportion of banks which are within 34 miles of the firm in distance. All independent variables are scaled by 1/100 Industry at the level of SIC 3 and year fixed effects are also controlled. Standard errors are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

Panel A: Junk vs. monitoring

	(1) hist. skin	(2) cov. int.	(3) ind. spec.	(4) dis. spec.	(5) local	(6) local
junk	2.522***	0.757***	0.757***	0.748***	0.398	-0.316
	(0.460)	(0.260)	(0.240)	(0.257)	(0.674)	(0.804)
size	-1.947***	-0.984***	0.0220	-0.0793		-0.478
	(0.173)	(0.0961)	(0.0727)	(0.0641)		(0.363)
leverage	-1.485*	-0.757	-0.520	0.344	-1.089	-1.035
	(0.897)	(0.557)	(0.446)	(0.450)	(1.740)	(1.739)
M/B	-0.805***	-0.696***	-0.0381	-0.121**	0.846	0.838
	(0.193)	(0.128)	(0.0767)	(0.0485)	(0.617)	(0.621)
R&D	11.68*	5.824*	6.769*	6.067***	16.86	16.24
	(6.982)	(3.471)	(3.674)	(2.293)	(11.37)	(11.53)
tangibility	3.232***	0.562	1.433**	0.948	-3.502	-3.684
	(1.245)	(0.753)	(0.711)	(0.706)	(2.389)	(2.404)
no. analysts	0.0496**	0.0106	-0.0137	-0.0118	0.0460	0.0669
	(0.0223)	(0.0111)	(0.0111)	(0.00909)	(0.0530)	(0.0522)
N	9104	9104	9104	9104	9104	9104
adj. R^2	0.625	0.932	0.186	0.147	0.139	0.139

Panel B: Spread vs. Monitoring

	(1) hist. skin	(2) cov. int.	(3) ind. spec.	(4) dis. spec.	(5) local	(6) local
loan spread	1.739***	0.374***	0.414***	0.532***	1.350***	0.00345
	(0.209)	(0.108)	(0.107)	(0.105)	(0.353)	(0.421)
size	-2.405***	-0.990***	-0.356***	-0.479***		-1.280***
	(0.133)	(0.0670)	(0.0832)	(0.0714)		(0.271)
leverage	-4.514***	-1.068***	-0.987**	-0.655*	-3.628***	-1.634
	(0.641)	(0.337)	(0.396)	(0.372)	(1.305)	(1.321)
M/B	-0.215	-0.312***	0.00972	0.0632	0.372	0.213
	(0.149)	(0.0681)	(0.0767)	(0.0746)	(0.298)	(0.303)
R&D	9.662***	3.503***	3.051***	4.333***	6.615*	4.636
	(3.019)	(0.878)	(1.032)	(1.126)	(3.411)	(3.360)
tangibility	1.650	0.984**	0.871	0.129	-4.179*	-4.851**
	(1.003)	(0.496)	(0.589)	(0.563)	(2.156)	(2.152)
no. analysts	0.0232	-0.0114	-0.0111	-0.0107	-0.0566	0.0359
	(0.0228)	(0.0109)	(0.0120)	(0.00987)	(0.0510)	(0.0520)
N	20230	20230	20230	20230	20230	20230
adj. R^2	0.555	0.924	0.111	0.098	0.068	0.072

in unilateral regressions, I do not put them in one regression to avoid the problem of multi-colinearity and difficulty in interpreting estimations. However, my proxies for monitoring skills are exempt from this concern and thus are put in one test because, except for historical skin, each of the other four captures one aspect of banks' monitoring advantage, which in principle can be independent of others.

$$Matched = a \times FinancialStrength \times Skills + b \times FinancialStrength + c \times Skills + controls$$

To test for symmetric matching, measures for firm financial strength and bank monitoring skills are demeaned so that the product of low value in credit quality and low value in monitoring ability will be as high as the product of high value in quality and high value in ability. The results are shown in the first two columns of Table 1.7. Most of the interaction terms are positively significant: firms with low (high) credit rating or high (low) loan spread and banks with high (low) historical skin, high (low) covenant intensity, high (low) industry specialization, high (low) distress specialization, and near (far) distance.[14] The last two columns also include the interaction term between firm size and bank size. The significant coefficient on that term confirms the well-documented fact that big banks tend to finance big firms while small banks lend to small firms. My coefficients of interest still hold, indicating that the story proposed has an orthogonal component that can explain more than just matching by size.

1.4.3 Switching

If the story proposed explains to some extent how a firm and a bank are matched in the loan market, it should also have implications on firms' switching to banks. Hence, I investigate whether the patterns of firms switching to new banks are consistent with my main theme as well.

[14]The exclusion of pairs in which the bank or firm does not ultimately find a counterpart would bias the estimation only if there were an omitted variable dictating the participation decision as well as the matching decision. Since I am measuring bank and firm fundamentals, I am relatively less concerned regarding this matter in this study than a typical study that uses a sample of "successfully matched" loans.

Table 1.7: Bilateral Matching Regression.

This table presents regression results where the dependent variable is a dummy indicating whether lender A gets a loan from borrower B in year t and main independent variables are interaction variables of borrower financial strength proxied by junk and loan spread and lender monitoring skills proxied by historical skin, covenant intensity, industry specialization, distress specialization and local, with financial strength and monitoring variables controlled. For any variable that has an interaction term with the other variable, both are standardized and scaled by 1/10. Firm and bank characteristics including firm size, M/B, leverage, number of analysts covering the stock, bank size, bank loan, bank profitability, and bank holding company dummy, whose coefficients are collapsed for brevity. The sample is at the level of borrower-lender pairs which are constructed by random matching between all banks and firms which engage in private loan activity in year t. Industry at the level of SIC 3 and year fixed effects are also controlled. Standard errors are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)
junk × historical skin	5.336***		1.970***	
	(0.422)		(0.396)	
loan spread× historical skin		3.556***		0.823***
		(0.164)		(0.122)
junk × covenant intensity	1.450***		3.161***	
	(0.328)		(0.347)	
loan spread× covenant intensity		0.646***		2.274***
		(0.122)		(0.121)
junk× industry specialization	1.627		1.747	
	(1.106)		(1.071)	
loan spread× industry specializatio		2.477***		2.450***
		(0.316)		(0.313)
junk× distress specialization	1.197***		0.560***	
	(0.213)		(0.203)	
loan spread× distress specialization		1.050***		0.497***
		(0.0703)		(0.0666)
junk× local bank	0.221		1.038	
	(2.410)		(2.393)	
loan spread× local bank		2.585***		3.192***
		(0.773)		(0.738)
firm size × bank size			0.798***	0.889***
			(0.0399)	(0.0176)
N	173504	450439	173504	450439
adj. R^2	0.214	0.140	0.221	0.159

First, I examine whether shocks to a firm's financial strength predict the firm switching to another bank. Financial strength shock by definition means a change in a firm's financial condition and, in reality, that may be a balance sheet shock, a shock to a firm's investment opportunities, or a liquidity shock. Furthermore, a firm's financing frictions are usually interconnected with its real side, and thus the real shock can also affect a firm's pledgeable income through its interaction with the firm's financing side; for example, a new project or a shock to an existing project may change its subjectivity to different financing frictions, such as moral hazard or the lack of contractibility.

Financial strength shocks, proxied by the absolute value of change in junk and loan spread, are used to predict a firm's probability of switching to a new bank. General firm characteristics, including size, M/B, and leverage, as well as year and industry fixed effects, are controlled.

$$Switched = a \times Shock + controls$$

Switched refers to the case in which the bank that grants a loan to a firm has not been associated with the firm before (i.e., not a relationship bank). I run the test at the level of firm-bank pair.[15] I define a relationship bank in a conservative way; specifically, a bank is a relationship bank to a firm if the bank has been in at least a one-year relationship with the firm no earlier than two years before the loan of interest is originated. The one-year designation captures the duration requirement for the bank's association with the firm; a bank in a relationship with a firm for a very short period can be little different from a new bank in terms of its familiarity with the firm. The "two years" requires the bank's past association to be relevant to the firm as of the time when the firm issues a new loan; firm conditions change over time and thus a bank would not view the firm as the identical entity with which the bank was associated long ago.[16] Firms with no relationship banks—those for which the questions from the analysis of switching are not defined—are dropped in

[15] I also check the results of the test run at the loan level in which I define *switched* by a percentage cutoff—50% for example—of banks that are not relationship banks; the results are robust to the choice of cutoff; in fact, the histogram of the proportion of relationship banks exhibits a very binary feature and implies its robustness.

[16] I have also tried (one year, one year), (two years, one year) and (two years, two years) to define a relationship bank, and the results are robust across these variants.

the sample. The results are presented in Table 1.8. With the exception of junk in (1) and (3), all others show consistent and statistically significant results. That is, the absolute value of change in firms' loan spreads predicts the probability of migrating to new banks. The evidence is consistent with the view that firms that are subject to shocks to their financial strength migrate to new banks. The weak evidence may be a result of low power because of insufficient time series variation on *junk*. Alternatively, it may imply that non-trivial switching costs exist. The implications from the static setting can be carried over to the dynamic setting only in the absence of any switching friction, which can make the firm-bank relationship stickier than it would be otherwise.

The second implication from the story on firms' switching behavior is that these switchers migrate to banks of a type commensurate with firms' financial strength shocks; that is, firms with negative shocks are more likely to switch to a bank with a high level of monitoring skills. To test this, OLS regressions are run in which the change in financial strength of the firm, proxied by junk and loan spread, is used to predict the level of monitoring skills of the switched bank, proxied by historical skin, covenant intensity, industry specialization, distress specialization, and proximity. General firm characteristics consisting of size, M/B and leverage, as well as industry and year fixed effects, are also included.

$$SwitchedToMonitoring = a \times NegativeShock + controls$$

As shown in Table 1.9, most of the coefficients of interest are consistent with the story: a drop in a firm's credit rating or an increase in a firm's loan spread results in high levels of historical skin, covenant intensity, industry specialization, and distress specialization, and in shorter distance from the bank to which the firm migrates. This finding yields evidence that a firm, conditional on receiving a negative shock, is more likely to migrate to a bank with high monitoring skills.

1.5 Discussion

1.5.1 Monitoring vs. Screening

As mentioned earlier, the notion of monitoring used in this paper also includes screening skills, namely, the ability to collect relevant information ex-ante and select firms with better financial strength. This subsection tries to distinguish between the two interpretations. Although screening banks usually select financially strong firms whereas monitoring banks proposed in this paper match with financially weak firms, these two will coincide if we have three types of firms. Specifically, suppose firms are of three types: financially strong, financially weak, and extremely financially weak. Financially strong firms are publicly observable, while the other two are pooled. Then normal banks still match with financially strong firms and screening banks can select financially weak firms from the pool.

The key difference between the two skills is that screening occurs before matching, while monitoring occurs after matching. Although theoretically separable, these two skills in the literature can scarcely be disentangled and probably coexist in reality. Some of the evidence in this paper is more consistent with monitoring than screening. Specifically, the covenant-based measure, covenant intensity, is more consistent with the notion of monitoring because covenants matter more after the contract is signed. Also, the extended setting in which a relationship bank refers its firm to a connected bank is also more commensurate with the story of monitoring. It is hard to believe that a relationship bank, which we usually believe to have more information, nevertheless cannot know the true type of its firm and has to present it to its connected bank for screening.

In any event, the ultimate objectives of screening and monitoring, though through different channels, are essentially the same, and that is to alleviate financing friction and improve the pledgeable income; one reduces the informational friction and the other the moral hazard, contracting friction, and coordinating friction. Therefore, for the purpose of this paper, I feel comfortable combining them and simply referring to monitoring skills in a broad sense.

1.5.2 Diversified Banks

Are those monitoring banks I propose less likely to be diversified banks and are normal banks more likely to be? In fact, the story suggests so in that these monitoring banks for motivation purposes usually need to put high skin in the game and therefore cannot be very diversified. This is in contrast to Diamond's (1984) study, in which the monitoring advantage of banks is endogenously derived from diversification and its implication for industrial organization is that optimally there should be one bank and thus no syndicated loans. I take the institutional features of banks as given and argue that bank monitoring ability is exogenously endowed and the right bank incentives to apply them come from higher skin in the game and the lack of diversification.

A concern may arise that part of the loan spread, which I use as a proxy for firm financial strength, in fact accounts for possible due compensation that monitoring banks ask for under diversification. As uncomfortable as it may seem, it in fact reinforces the story in that the premium for lack of diversification is an additional implicit servicing cost that the firm must bear in order to call for monitoring skills. Firms that are willing to pay the extra cost are those that really need and value these skills. Certainly, motivating monitoring skills is not cost free, and such cost of lack of diversification will ration firms with too weak financial strength and result in inefficient under-borrowing.

1.6 Conclusion

This paper characterizes banks by their monitoring skills and demonstrates with evidence that firms with low financial strength are more likely to match with monitoring banks. This study is helpful in understanding a well-documented fact in the literature that big banks tend to grant loans to well-established firms, while small banks tend to finance small firms. Large firms are usually believed to be less financially constrained than small firms. My study suggests that small banks, which are less diversified, are more likely to be monitoring banks. In this way, large firms will get funding smoothly from big banks, while small firms will have to turn to small banks for more discipline for financing. Furthermore, the mechanism has its own value beyond just explaining the matching by size. After controlling for size, the effect implied by the proposed mechanism still stands.

Although the paper attempts to address a general question on firm-bank matching as a function of different bank specializations, each can be investigated even further and in much greater depth in the future; for instance, how do distress monitoring banks behave differently from other banks, what can industry monitoring banks do specifically that others cannot, and how can a local bank take advantage of its local firms? Understanding heterogeneous bank skills may also open a window for understanding the function of banks in general. Moreover, further examinations of the implicit switching cost—for instance, how it varies with firm fundamentals, with relationship bank fundamentals, or with connected bank fundamentals—is left for future research.

This paper serves to investigate a first-order question that with no matching friction whether the implication for capital structure in the loan market can be born out in the data. In particular, in investigating firms' switching behavior, an implicit assumption is made that no (severe) switching friction exists so that the implications for the matching in a static setting can be carried over to the switching in a dynamic world. A switching friction and its implication for the loan market are ignored in this paper and therefore are left for examination for future research.

Table 1.8: Switching Probability Regression.

This table shows a linear probability regression where financial strength shocks, proxied by the absolute value of change in junk and loan spread are used to predict a firm switching to a bank. General firm characteristics including size, M/B and leverage are included. All columns run regressions using the sample at the level of firm-bank pair where the dependent variable is one if the bank originating the loan is not a relationship bank. Firms with no relationship banks are dropped in the sample. The bank is a relationship bank to a firm if the bank had been in at least a one-year relationship with the firm no earlier than two years before the loan of interest. Junk is a dummy indicating a firm with S&P rating lower than BB and loan spread is the natural logarithm of the amount the borrower pays in basis points over LIBOR for each dollar drawn down including any annual (or facility) fee paid to the bank group. Size is the natural logarithm of the total sales of the borrower. Leverage is the book leverage and M/B is the market-to-book ratio. Industry at the level of SIC 3 and year fixed effects are also controlled. Standard errors are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)
$\mid \Delta$ junk $\mid$	2.944*	1.932		
	(1.568)	(1.536)		
$\mid \Delta$ loan spread$\mid$			7.996***	8.012***
			(0.754)	(0.726)
size		-5.318***		-5.689***
		(0.336)		(0.201)
M/B		1.302**		0.911**
		(0.586)		(0.408)
leverage		-4.739**		-7.316***
		(2.372)		(1.616)
N	33632	33632	49923	49923
Industry&Year FE	YES	YES	YES	YES
adj. R^2	0.053	0.072	0.045	0.080

Table 1.9: Switching: Whereto.

This table shows results of OLS regressions where change in financial strength of the firm proxied by junk and loan spread, is used to predict the level of monitoring skills of the bank, proxied by historical skin, industry specialization, distress specializations and local, to which the firm is switched. General firm characteristics including size, M/B and leverage are included. Junk is a dummy indicating a firm with S&P rating lower than BB and loan spread is the natural logarithm of the amount the borrower pays in basis points over LIBOR for each dollar drawn down including any annual (or facility) fee paid to the bank group. A switching firm is defined as one being not getting a loan from a relationship bank. The bank is a relationship bank to a firm if the bank had been in at least a one-year relationship with the firm no earlier than two years before the loan of interest. Firms with no relationship banks are dropped. Historical skin is the average allocation in percentage the bank invests in all its syndicates of the past five years. Covenant intensity is a bank's average covenant strictness on its previous contracts signed, where I follow Murfin (2012) to compute a loan contract's covenant strictness. Industry specialization is the bank's capital in percentage in the portfolio of loans originated over the past five years which is allocated to firms of the same SIC3 to the firm of interest. Distress specialization is the bank's capital in percentage in the portfolio of loans originated over the past five years which is allocated to financially distressed firms, which are defined as firms of the top quintile of industry-year adjusted ww Index. Local bank is a dummy equal to one if the bank is within 34 miles of the firm in distance and zero otherwise. Industry at the level of SIC 3 and year fixed effects are also controlled. Standard errors are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the loan level.

Panel A: Junk vs. Monitoring

	(1) hist. skin	(2) cov. int.	(3) ind. spec.	(4) dis. spec.	(5) local
Δ junk	2.651***	1.743***	0.705**	1.172**	1.954**
	(1.028)	(0.672)	(0.346)	(0.570)	(0.953)
size	-2.780***	-0.957***	0.116	0.131	-0.194
	(0.192)	(0.142)	(0.123)	(0.0817)	(0.247)
M/B	-1.824***	-0.409*	-0.223	-0.460***	-0.0841
	(0.349)	(0.222)	(0.218)	(0.115)	(0.420)
leverage	9.275***	3.604***	0.543	2.953***	-1.130
	(1.413)	(0.972)	(0.910)	(0.713)	(1.535)
N	7202	7307	5078	6191	6922
Industry&Year FE	YES	YES	YES	YES	YES
adj. R^2	0.243	0.710	0.101	0.116	0.102

Panel B: Spread vs. Monitoring

	(1) hist. skin	(2) cov. int.	(3) ind. spec.	(4) dis. spec.	(5) local
Δ loan spread	1.073***	0.326*	-0.0956	0.271*	-0.246
	(0.299)	(0.178)	(0.160)	(0.153)	(0.303)
size	-3.540***	-1.313***	-0.198**	-0.482***	-0.965***
	(0.125)	(0.0822)	(0.0796)	(0.0764)	(0.137)
M/B	-1.706***	-0.736***	-0.297**	-0.603***	-0.546**
	(0.222)	(0.138)	(0.116)	(0.106)	(0.263)
leverage	3.111***	1.449**	-0.487	1.453**	0.684
	(0.958)	(0.602)	(0.574)	(0.573)	(1.088)
N	12735	12937	8995	11279	12355
Industry&Year FE	YES	YES	YES	YES	YES
adj. R^2	0.286	0.719	0.098	0.102	0.068

Chapter 2

Bank Inter-Connection and Information Transmission: Evidence from Syndicated Loans

2.1 Introduction

A characteristic feature of the private loan market is its opaqueness in terms of borrowing firms' information, as compared to the public bond and stock markets. It is important to understand how such informational frictions affect a firm's borrowing behavior. In particular, relationship banks' ability to extract firms' economic rent from their informational advantage (e.g., Sharpe, 1990; Rajan, 1992) increases a firm's cost of switching to a new bank and impedes its efficient migration.

In this paper, I study how loan syndication generates a coordinating mechanism among syndicate members and improves firms' migration through information transmission. Specifically, I propose that the syndicating process cultivates trustful business relationships through which the linked banks can share information candidly and, when a relationship bank is not a best fit to its firm, under certain conditions, the bank has an incentive to transfer the firm to its connected bank.

Over the past two decades, syndication has taken over traditional bilateral financing and become a predominant way of originating deals in the loan market (e.g., Chui, Domanski, Kugler, and Shek, 2010; Gatev and Strahan, 2009). Syndicating a loan by its nature is a cooperative activity and thus should increase the opportunities of a lender to communicate with other members. Hochberg et al. (2007) find evidence that venture capitalists that co-finance a firm's project share information about future sound deals and emphasize the importance of studying venture capital from a network perspective. In contrast, only limited studies on information transmission are reported in the literature on loan syndication, and all of them have investigated sharing information about the firm of the syndicate (e.g., Lin, Ma, Malatesta, and Xuan, 2012). Also, papers involving such analysis tend to focus on the conflicts of interest between syndicate partners and their resulting negative effect on information sharing, such as the free-rider problem (e.g., Shivdasani and Song, 2011; Anand and Galetovic, 2000) and coordination failure (e.g., Brunner and Krahnen, 2008; Hertzberg, Liberti, and Paravisini, 2011). The possible positive effect of syndication on information dissemination has not been discussed in the literature to the best of my knowledge. Furthermore, the related literature has usually focused on the borrower's side and treated lenders identically (e.g., Sufi, 2007; Ivashina, 2009). However, banks, like firms, differ in their type and in cases when a bank plays an active investor's role, its own abilities (e.g., monitoring skills, industry specializations, and advising ability), will also affect the pledgeable income of the project to be financed. I aim to add to the literature by investigating how informational frictions in the presence of bank heterogeneity result in inefficient financing and how the coordinating mechanism created by syndication can alleviate switching frictions and restore efficiency.

Why a connected bank ever has an incentive to give up its informational advantage and share information with another bank is not a trivial consideration. To illustrate my idea how bank heterogeneity sometimes creates such an incentive, I build a simple static model, where a firm can be of three types: a good type with a positive net present value (NPV) project or medium and bad types with equally negative NPVs. The economy includes banks of two types that can finance a firm's project, a normal bank or a monitoring bank with monitoring skills. The only difference between a medium and a bad firm is that a medium firm's project can be made profitable by a monitoring bank that monitors the firm. I assume that banks are randomly matched into pairs, a simplifying assumption which can represent their previous syndicating experience, and build a business relationship, which can work as a mechanism through which connected parties communicate information and also punish those that intentionally send incorrect information. Bank ties and bank type are observable throughout. In the first period, firm type is assumed to be observable for simplicity; however, in the next period, firms receive shocks such that the firms can turn into other types, and no banks other than their relationship banks can observe those shocks. Relationship banks decide whether to finance the firms a second time.

I find that the equilibrium is characterized by a normal bank under some conditions transferring its medium firm to its monitoring-type connected bank and a monitoring bank occasionally migrating its good firm to its normal partner. The intuition is straightforward: When matching inefficiency can be resolved by firm referral, all associated parties (i.e., the relationship bank, the connected bank, and the firm) can be better off by extracting some share of the gained surplus and thus are willing to do so. Specifically, a normal bank is willing to give up its medium firm in hand, which it would have to drop anyway, to its monitoring partner that is capable of working with the firm, and then both banks can request a share of the increased surplus. Similarly, if possible, a monitoring bank must also be willing to refer its good firm to its normal-type connected bank which is a better fit and thus make use of its capacities more effectively elsewhere. Also, the firm in question must always be willing to be transferred to a suitable bank without taking the risk of looking for funding in the market, which would view its leaving as a negative signal and refuse to grant a new loan.

Furthermore, the model generates three testable implications: (1) The magnitude of a private shock to firm credit quality predicts a firm's probability of going to a connected bank, (2) a negative private shock predicts that the connected bank to which a firm switches has a high probability of being a monitoring type, and (3) as compared to a positive private shock, a negative shock is associated with a high probability of a firm migrating to a connected bank.

To test the model's implications, I use the dataset of SDC DealScan on loan syndicates and rely on syndicating relationships to measure bank connection. For each loan, I identify the lender by whether it had before granted a loan to the firm (i.e., a relationship bank) and by whether it had ever been a syndicate partner of a relationship bank if it is not a relationship itself. Next, I follow the practice commonly applied in the literature of using regression residuals to proxy for private information (e.g., Acharya, 1988; Chiappori and Salanie, 2000; Song, 2004) and obtain the loan spread residual from a spread-predicting regression. I argue that the spread residual should capture ex-ante private information that the relationship bank has about firm credit quality. By definition, the relationship bank's private information is obtained through its lending relationship with the firm and is not known before the relationship is created. Hence, that private information is essentially an informational shock to the relationship bank.

The first implication suggests that if the relationship bank finds the information update to be very large, it is more likely to refer the firm to its connected bank.

I find consistent evidence that the magnitude of the spread residual predicts a firm's probability of switching to a connected bank. Also, when the residual is big (i.e., a negative shock), the connected bank to which the firm migrates is more likely to put high skin in the game, indicating its monitoring role. Furthermore, consistent with the third implication, in the sub-sample where a firm gets a loan either from a relationship bank or a connected bank, I find that the spread residual is positively associated with a firm's probability of selecting a connected bank. All these findings confirm the model's predictions and suggest that relationship banks play an important role in firms' migration by referring firms to connected banks when the relevant information on quality is not publicly observable.

A firm's switching cost is usually defined as the cost that a firm has to bear (pecuniary or non-pecuniary) of switching to another bank for funding in addition to its fair cost of capital. The switching cost in the private loan market can be economically large. For example, Kim et al. (2003) builds a repetitive consumer-producer model with a fixed cost of choosing a different firm and applies the model to the data on bank loans, in which they find the point estimate of the average switching cost is 4.1%, about one-third of the market average interest rate on loans. The finance literature tends to relate switching costs to the economic rents that banks can extract. For instance, Degryse and Ongena (2005) report evidence on the occurrence of spatial price discrimination in bank lending due to banks' different geographic advantage. The most well-known switching cost investigated in the theoretical literature is adverse selection in which case relationship banks can then hold firms up from their informational advantage (e.g., Sharpe, 1990; Rajan, 1992), and the theoretical conjecture is also supported by plenty of empirical evidence that, for example, previous lending relationships with a firm lead to a high probability of future lending to the firm, especially when it faces high information asymmetry (Bharath et al., 2007; Barone, Felici, and Pagnini, 2011). The paper that is more related to my study is Gehrig and Stenbacka (2007)'s, in which the authors exogenously model lenders' information sharing and show its benefit (i.e., fostering the ex-post lending efficiency) as well as its potential cost (i.e., relaxing the ex-ante competition for forming banking relationships). My study discusses a simple scenario in which sharing information can endogenously occur in equilibrium reducing switching costs and Pareto-improving both lender's and borrower's well-being and then tests the implications with real data.

This paper is generally related to three strands of literature. Specifically, it explores circumstances under which a lender coordinates with its partner and reduces firms' switching frictions, as opposed to banks holding onto their proprietary information to extract economic rents only and aggravating switching difficulties, on which the related literature tends to focus (Karceski, Ongena, and Smith, 2005; Degryse, Masschelein, and Mitchell, 2010). Also, this study looks at the bright side of syndication, which is to generate a coordinating mechanism through which syndicate members can commit to transmit information truthfully, and adds to the literature on loan syndication (e.g., Pichler and Wilhelm, 2001; Song, 2004). In addition, the paper demonstrates a new value-added role of relationship banks, which is to migrate deals and restore the local efficiency of firm-bank matching, and thus the study contributes to the literature on relationship banks (e.g., Boot, 2000; Ongenah and Smith, 2000).

The remainder of the paper is organized as follows. Section 2.2 elaborates my fundamental idea with an illustrative model and develops testable implications. Section 2.3 describes the data, and explains the sample and variable construction. Section 2.4 explains the empirical methodology and details the results while Section 3.5 concludes.

2.2 Model

I build a parsimonious model to illustrate the main idea. Subsection 2.2.1 describes its setup and subsection 2.2.2 characterizes the equilibrium and derives its implications, whose proofs are in the appendix.

2.2.1 Setup

The model features possible inefficient firm-bank matching, which is hard for the market to resolve due to informational frictions. The relationship bank that observes its firm's private information but is stuck with an inefficient matching has an incentive to refer the deal to another bank that can both restore the matching efficiency and trust the relationship bank's private information.

To model this idea in the simplest manner, I assume a two-period economy with two types of players: banks and firms. There are two types of banks, normal banks with a probability of $1 - m$ and monitoring banks with a probability of m, and the bank type is publicly observable and persistent over time. On the other hand, firms look for funding and can be of three types: good, medium, and bad.[1] Banks have capacity constraints in that each bank each period is endowed with only one unit of capital.[2] Every firm has a short-lived project available at $t = 1$ and $t = 2$, each requiring fixed capital, which I normalize to be one, and will yield x with a probability of q or zero otherwise. Firms differ in their qs, the good with q_g and the medium and bad with q_b. [3] Only good projects are profitable, that is, $\pi_g = q_g x - 1 > 0$, and $\pi_b = q_b x - 1 < 0$. Medium-type firms can be monitored with a cost of c and then turned profitable with $q_m < q_g$ and $\pi_m = q_m x - 1 - c > 0$. In addition, I assume that $\frac{q_m + q_b}{2} x - 1 - c < 0$, which implies that no monitoring bank is willing to finance a firm with equal probabilities of being medium and bad.

At $t = 0$, banks are randomly matched into pairs, independent of their type, and each has a connected bank. This is a simplifying assumption which can represent the banks' previous syndication experience.[4] Matched banks have a mechanism for sharing information with each other and also for punishing the partner that intentionally provides incorrect information. Again, this is a reduced-form assumption which can be motivated by a repeated game setting or a dynamic setting of the reputation mechanism. In this simplistic model, information transmission is costless while a more realistic setting may involve some form of communication cost, which, for example, can be a result of conflicts of interest between bank partners. Bank ties are publicly observable.

At $t = 1$, firms go to the loan market for financing. For simplicity, I assume firm type is initially observable.[5] At $t = 2$, each firm receives an independent shock that transforms its type into good, bad, or medium with equal probability.[6] This

[1] A more general assumption on the distribution of firm type does not change the model's qualitative results.

[2] The alternative assumption of no capacity constraint would simplify the analysis even further, at the expense of elegance though.

[3] As long as a medium project makes a negative profit, though different from the bad project's, my conclusions remain the same.

[4] A more general assumption on how banks are matched does not change my conclusions.

[5] A more general assumption that complicates the model's solution would not affect the main implications.

[6] A general assumption about the distribution of new firm type or a different conditional shock

shock can only be observed by the firm and its relationship bank. In this simple model, although initially observable, firm type is not persistent so the shock to the firm, which is assumed not to be publicly observable, is also a shock to the bank's information set. Alternatively, it can be interpreted that firm type is persistent and nevertheless only observable to the firm initially, in which case under the first round of matching, only the expected value of firm type is known to banks. Also, in the second period, the relationship bank will realize its firm's true type privately, and the differences between the prior and the updated belief is effectively an informational shock to the bank. Although conceptually distinguishable, these two cases have little difference in effect, at least so far as this chapter is concerned. After observing the shock, the bank decides whether to finance its firm that was matched in the first period, share the information with its connected bank, or leave it to the market.

Furthermore, I assume that all agents are risk-neutral, the market return required by banks is zero, long-term contracting is not feasible.[7]

See the timeline in Figure 2.1.

2.2.2 Implications

This subsection describes the equilibrium of the model and derives its testable implications. The equilibrium at $t = 1$ is obvious: The same number of firms as banks' will participate in the loan market and get financed with m percent of them being medium firms and financed by monitoring banks and $1 - m$ percent of them being good firms and financed by normal banks, given that firm type is observable. In fact, if there are more qualified firms than banks, the market will be clear at a positive required rate of return by banks, which I have normalized to be zero. At $t = 2$, the equilibrium will be characterized by the following implication.

Implication 2.2.1. *A pure strategy equilibrium at $t = 2$ exists such that (1) a bank that is connected to a bank of the same type never shares information, (2) a normal bank which is connected to a monitoring bank, shares its information with*

distribution does not affect my main implications.

[7]As private information in the second period is not publicly observable, it is therefore not contractible ex-ante. Even if it is, I conjecture a long-term contract regardless whether it is renegotiation-free should not change the implications qualitatively.

- $t = 0$: Banks are randomly paired.
- $t = 1$: Each bank selects a firm's project to finance.
- $t = 2$: Each firm gets a shock, which is only observable to its relationship bank, which has to decide whether to finance the firm a second time, share it with its connected bank, or leave it to the financial market.

Figure 2.1: Timeline.

its bank partner when its firm becomes a medium type and its connected bank is not matched with a medium firm, (3) a monitoring bank which is connected to a normal bank, shares its information with its bank partner when its firm becomes good and its connected bank is not matched with a good firm, and (4) normal banks only take good firms while monitoring banks take medium firms as well as good firms when they cannot transfer the firm to their connected banks.

Implication 2.2.1 is highly intuitive: Banks have an incentive to share information if they can resolve some friction and gain a synergy from which everyone can be made better off. The only friction in this model is the inefficient matching of banks and firms, which happens when a normal bank has a medium firm in hand or a monitoring bank has a good firm in hand. Such inefficient matching can be resolved if the relationship bank in question is connected to a different bank that fits its firm's type and if its connected bank's capital constraint is not binding. Put simply, migration only takes place if the connected bank is a better fit to the relationship bank's firm and also has a "slot". The way for relationship banks to effectuate their compensation for referral is not modeled here but could be achieved through a direct side payment, co-syndicating, or receiving a referred deal in the future.

The implication that firms prefer to be transferred to connected banks if switching is necessary can be generalized to a setting where both types of information about firm financial strength coexist (i.e., observable and unobservable information). As long as relationship banks are believed to have more information than non-relationship banks, the adverse selection problem will cause firms to be downgraded if they leave their relationship banks for new banks from the market.

Next, I will generate implications that can be made into testable hypotheses.

Implication 2.2.2. *At $t = 2$, given a firm being financed, a shock predicts the firm's high probability of going to a connected bank.*

The intuition is straightforward that only a shock creates a wedge between firm type and bank type and only private information necessitates a referral to a connected bank. The bigger the private shock, the more inefficient the matching will be and the more likely the relationship bank will refer the firm to its connected bank. Definitely, if the shock is too big (e.g., a very negative shock), then the firm will be eliminated from the market and not be a "legitimate" player for the question of interest.

Implication 2.2.3. *At $t = 2$, given that a firm goes to a connected bank, a negative shock predicts a monitoring bank while a positive shock predicts a normal bank.*

Implication 2.2.3 is consistent with the equilibrium characterization in implication 2.2.2. A negative shock, which makes a firm deteriorate in quality, is more likely to be transferred to a monitoring bank if at all, while a positive shock is more likely to remove a firm's need for monitoring and migrate it to a normal bank. As transferring to a connected bank is not always possible, the next implication follows.

Implication 2.2.4. *At $t = 2$, given that a firm gets financed, as compared to a positive shock, a negative shock is associated with a higher probability of going to a connected bank.*

This implication is not overly intuitive, and it is easier to explain it if I paraphrase the implication in this way that connected banks are more likely to be associated with lower-quality firms while relationship banks are more likely to be associated with higher-quality firms. Put simply, relationship banks have higher-quality firms than connected banks. Even with relationship banks' ability to share information with their connected banks, in equilibrium we do not have a global first best as some bank-firm matching is still inefficient. In this particular model, this is for two reasons. First, bank-bank matching at $t = 0$ is not always efficient from the perspective of the second period firm-bank matching. As a result, there are cases in which a relationship bank has no appropriate connected bank (i.e., a bank's being connected to another of the same monitoring type). Second, banks face a capacity restriction, and when a connected bank's constraint is binding, transferring a firm is not feasible. Because of these two imperfections, some medium firms are unfortunately rationed by their relationship banks whereas good firms can always stay with their relationship banks regardless of their type. In contrast, whenever a firm is transferred to a connected bank, bank-firm matching is always efficient, which implies no inefficient credit rationing occurs. Therefore, on average, better firms stay with relationship banks and firms that deteriorate in quality are more likely to be associated with a connected bank.

The interpretation above in fact can be more general. Connected banks can behave as relationship banks. Suppose that banks are well connected in the sense that a monitoring (normal) bank can always find a connected monitoring (normal) partner and also that no friction exists between two connected banks (i.e., no capacity constraint, no communication cost, and no coordination friction). With these two extreme conditions satisfied, information can be shared and deals can flow freely between relationship banks and their connected banks. Both relationship banks and connected banks are equally informed and matched with firms equally efficiently, and then they are essentially the same. In this way, a connected bank can be seen as an indirect relationship bank.

However, neither condition can be perfectly satisfied in reality. Banks are not necessarily connected in a perfectly complementary way, and their inter-connections may exhibit some homophily. When a bank finds itself to be unfit for the firm, it is likely that its connected bank is also not a fit, and then the firm may be rationed inefficiently. Also, both communication and coordination are costly, and conflicts of interest may stop two linked banks from transferring deals effectively. For example, the economic rent that a monitoring relationship bank can obtain by holding up a good firm may prevent the bank from referring the firm, even though the relationship bank has a normal bank partner. Therefore, a relationship bank in equilibrium should still have an informational advantage over a connected bank and do business with better firms.

2.3 Data

Next, I examine whether implications 2 through 4 are consistent with what we observe in the data. I mainly use the LPC DealScan bank loan dataset to identify bank syndication and loan terms. I extract all U.S. loans from 1988 to 2006 and drop loans whose starting date and duration is not known. I trace back to each bank's and company's ultimate parent if it has one and that information is available.

I assume that within a syndicated loan two banks build a business relationship if at least one is a lead bank, and this relationship starts with the loan and ends when the loan matures. Usually non-lead banks play an extremely passive investing role and engage in limited communication. Following Bharath et al. (2007) and Gatev and Strahan (2009), I define a bank as a participant if the word "participant" appears in the role of the lender and as a lead bank otherwise. Furthermore, given the active role of lead banks in syndicating a loan, I assume that only lead banks' information matters for initiating a loan and its terms. In non-syndicated loans, the only bank will be defined as the lead bank no matter what role it plays.

I construct two variables to describe the relationship between a lending bank and a borrower: *relationship*, an indicator identifying whether it is a relationship bank to the firm or not, and *connected*, a dummy indicating whether it is a connected bank of a relationship bank. I define a relationship bank in a conservative way; specifically, a bank is a relationship bank to a firm if the bank has been in at least a one-year relationship with the firm no earlier than two years before the loan of interest is originated. The one-year designation captures the duration requirement for the bank's association with the firm; a bank in a relationship with a firm for a very short period can be little different from a new bank in terms of its familiarity with the firm. The "two years" requires the bank's past association to be relevant to the firm as of the time when the firm issues a new loan; firm conditions change over time and thus a bank would not view the firm as the identical entity with which the bank was associated long ago.[8] A connected bank is defined as one that is not a relationship bank to the firm but has been in a relationship with one of the firm's relationship banks. I use the sample of 1994-2006 in all tests so each firm has a considerable period of loan history to identify the set of relationship banks and their connected banks as completely as possible. Following Campello et al. (2011), I also construct such loan characteristics as loan size, maturity dummies, performance pricing indicator, loan purpose, and loan type dummies, supplemented with monthly market credit spread and term spread.

I use the linking table provided by Chava and Roberts (2008) to match with borrowers' financial information in Compustat. Constructed firm-level controls include leverage, market-to-book ratio, profitability, size, tangibility, and research and development (R&D); Refer to Table 2.1 for detailed definitions of loan and firm characteristics.

I also manually match banks from DealScan to the Bank Regulatory Database from the Wharton Research Data Service (WRDS). Specifically, I use a text-matching algorithm to perform a mechanical matching based on name, state, zip code, and the implied operation window from loans data, and then check each match manually. I then hand-match the remaining banks by name. When it comes to multiple candidates for matches (i.e., those with identical names), I check state, zip code, and the operation window to pin down the exact match. I match names at both the parent level and the subsidiary level. For parents, I start with the bank holding company database and try the commercial bank database if I cannot find the parent, and vice versa for subsidiaries. I have successful matches for 477 parents and 852 subsidiaries. Given that this matching process often involves discretion, I use these data only if they are necessary to construct my main variables of interest or to control for potential endogeneity problems.

2.4 Results

The model implies an important role of connected banks in firm financing and therefore I expect these banks to be active players in the loan market. In fact, I

[8] I have also tried (one year, one year), (two years, one year) and (two years, two years) to define a relationship bank, and the results are robust across these variants.

find the data to be consistent with this conjecture that 90% of switchers migrate to a connected bank. This high frequency of connected banks among switchers implies that connected banks do play a predominant role in facilitating efficient migration. A concern regarding this result may arise that the banks in my sample are simply too connected. I believe that this case is unlikely to be true in my data. First, I define *relationship bank* and *connected bank* in a highly restrictive way such that it is not easy to be a "special" bank to a firm. Also, I check the entire sample that has thousands of financial intermediaries and find on average one institution only has 6 connected partners. Therefore, I believe that it is little possibility that banks are so connected that whatever bank to which a firm switches, it will be a connected bank mechanically. Furthermore, this high percentage indicates a very small proportion of firms that leave their relationship banks and successfully get new loans from banks in the market (only 10% among all switchers). This demonstrates that firms that can neither stay with relationship banks nor be referred to connected banks are dropped by the market, implying that these firms indeed have very weak credit quality and that their efficient matching should be with no bank. This particular finding reinforces the validity of the model's idea that avoidance of being pooled with really bad firms is the fundamental reason why firms are willing to migrate to connected banks.

Another interesting fact is that the magnitude of firm spread change has a positive correlation of 0.134 with the likelihood of the firm migrating to a connected bank. A big spread change indicates a big change in the firm's credit quality, and its resulting bank migration implies that banks are heterogeneous just as firms are, and a change in firm financial strength thus leads to a different matched bank. In addition, it is connected banks to which such firms migrate, which is consistent with the conjecture that the change in firm quality is not completely publicly observable and therefore connected banks, which have informational advantage thanks to their relationship banks, can step in and take over a deal.

Next, I turn implications 2 through 4 into hypotheses and perform rigorous testing for each of them. All these implications involve private information. To understand the role of private information here better, consider two simple scenarios: First, ex-ante firm credit quality is observable, but over the course of the loan, the firm receives a shock to its credit quality and, other than the firm itself, only the relationship bank observes it and, second, ex-ante firm credit quality is unobservable and remains fixed over time, but the relationship bank receives a private signal and updates its priors on firm credit quality. In the first situation, the private information concerns the actual shock to firm credit quality. The theory models the first scenario, and in the second case, the private information relates to the relationship bank's update on firm credit quality and thus a shock to the bank's information set. For the relationship bank, the two cases make no difference, as the private information it obtains from the lending relationship is always viewed as an informational shock to the bank itself.

However, by definition, such private informational shocks are not publicly observable. To measure them, I construct *spread residual*, the residual term of an ordinary least squares (OLS) regression in which I use publicly observable variables to predict loan spread. The practice of using regression residuals as a proxy for ex-ante private information is common in the literature (e.g., Acharya, 1988; Nayak and Prabhala, 2001).[9] The spread is an equilibrium outcome and determined after the bank-firm matching occurs and therefore the part that cannot be explained by ex-ante observables should be unobservable ex-ante to market participants other than insiders, namely the firm and its related banks. Specifically, I use an exhaustive list of regressors including firm size, market to book ratio, leverage, profitability, tangibility, monthly credit and term spreads, Altman's Z score, cash flow volatility, loan size, performance pricing, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies, and year and firm fixed effects. Loan characteristics and firm fixed effects are arguably associated with private information as well. However, to be conservative, I still put them as predictors so that I can to the greatest extent control for public soft information, which is observable ex-ante but cannot be captured completely by hard financial variables. This regression yields an R squared of 86% (in Panel A of Table 2.1). Then I am relatively confident that the spread residual will capture a great deal of private information.[10] I have tried less conservative spread residuals, and the results from residual analysis remain qualitatively similar.

Implication 2.2.2 states that a big private informational shock predicts a high

[9]In these studies, usually the residuals from the self-selection stage outcome are used as a proxy for private information to explain the second-stage characteristics; in that sense, I am using the residuals from the "second-stage" to explain the "first-stage" matching process.

[10]Certainly, not all private information of the relationship bank will be incorporated into the loan spread ex-post and, therefore, the spread residual only captures part of all the information.

probability of a firm switching to a connected bank, and I derive the following hypothesis,

Hypothesis 2.4.1. The magnitude of the spread residual positively predicts a firm's probability of going to a connected bank.

Based on this hypothesis, I run a linear probability regression with the specification as follows,

$$C = \beta_1 \times \mid residual \mid + controls.$$

C is a dummy variable which is equal to one if the bank is a connected bank and zero otherwise. β_1 is expected to be positive to be consistent with Hypothesis 2.4.1. Panel B of Table 2.1 presents OLS regressions predicting a firm's probability of migrating to a connected bank using the absolute value of spread residual with the sample of loans. To test this hypothesis in a more conservative and cleaner way, I use the sample where all lead banks are relationship banks, connected banks or new banks. A new bank is defined as neither a relationship bank nor a connected bank of the firm. The sample in which a firm had no relationship bank before is dropped. Column (1) includes such firm-level controls as size, M/B and leverage, profitability, and tangibility. Column (2) also adds more controls, including Altman's Z score, cash volatility, loan size, credit spread, term spread, performance pricing, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies, and industry and year fixed effects. Both columns show that the magnitude of the spread residual predicts a firm's probability of switching to a connected bank. This is consistent with the model's implication that when a relationship bank observes a big informational shock to its firm's credit quality, it may refer the firm to its connected bank.

The story of firm referral by relationship banks can assure its validity if the spread residual really captures private information, as referral in principle is only necessary when private information is involved. However, the inability to differentiate private information from soft information that is observable to the agents in question but not to econometricians necessitates consideration of an alternative story. For example, suppose that banks with similar monitoring expertise syndicate loans together, and a shock migrates a firm to another bank with a similar level of monitoring expertise, which is also more likely to be a connected bank. This story would be consistent with this table but would not involve bank referral. However, the story is only seemingly plausible in that it has a firm receiving a shock to credit quality and switching between banks with similar monitoring expertise, implying that a firm's credit quality has little association with a bank's monitoring expertise, which contradicts the previous findings.

However, one may argue that this alternative story would still be true if the results regarding connected banks came from observations in which a firm receives a small shock and migrates to a new bank with only a little different level of monitoring expertise. I perform a robustness check with the continuous variable spread residual replaced with a dummy by the cutoff of its median, which should mainly capture large shocks in the sample, and find that the results still hold qualitatively. Though being unlikely itself, that alternative story brings out a more general endogeneity concern that may be true when there is an omitted variable that determines the bank-bank matching as well as the firm-bank matching. However, as usual, it is difficult to address this concern unless we know what the omitted variable or the alternative story is. The story of relationship banks referring firms to connected banks because of information asymmetry is the simplest and most natural one that can be proposed as consistent with this table and the later findings. Last, I follow a very conservative definition of relationship bank and connected bank in the sample. On average, a firm in the sample has six relationship banks and a bank has five connected fellows. Therefore, it is not likely that the finding is simply mechanical as a result of virtually all banks being connected.

Implication 2.2.3 states that if a firm goes to a connected bank because of a negative private shock, then its connected bank is a monitoring type. However, monitoring is not observable to econometricians although this may be publicly known or expected. Monitoring takes a bank effort, time, and resources and therefore should be motivated appropriately to occur. Following the literature on moral hazard (e.g., Khorana, Servaes, and Wedge, 2007; Demiroglu and James, 2012; Chemla and Hennessy, 2014), I argue that, for incentive purposes, monitoring banks are expected to put considerable skin in the game. Specifically, I use a bank's percentage allocation in a syndicate to represent its skin in the game, by which I proxy for a bank's degree of monitoring activity. Given that the spread residual is negatively associated with the extent of a negative shock, I derive the next hypothesis:

Table 2.1: Connected Bank vs. Spread Residual Magnitude.

The table presents OLS regressions in Panel B with the sample of loans where all lead banks are either all relationship banks, connected banks or new banks. The dependent variable is a dummy indicating the switching to connected banks and the main independent variable is spread residual, computed from the residual terms of an OLS regression in Panel A where I use publicly observables to predict loan spread. These predictors include size, M/B, leverage, profitability, tangibility, credit spread, term spread, Altman's Z score, cash flow volatility, loan size, performance pricing, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies, year and firm fixed effects. Connected bank is a bank which is not a relationship bank to the firm but has been in a relationship with one of the firm's relationship bank. Two banks are in a relationship if they are syndicate partners in a loan where at least one bank is a lead bank. The bank is a relationship bank to a firm if the bank had been in at least a one-year relationship with the firm no earlier than two years before the loan of interest. A new bank is one being neither a relationship bank nor connected bank though the firm himself has relationship bank available. Loan spread is the natural logarithm of the amount the borrower pays in basis points over LIBOR for each dollar drawn down including any annual (or facility) fee paid to the bank group. Size is the natural logarithm of the total sales of the borrower. Leverage is the book leverage and M/B is the market-to-book ratio.Leverage is the book leverage and M/B is the market-to-book ratio. Tangibility is the borrower's property, plant and equipment divided by total assets. Credit spread is monthly spread of the yield of Moody's Aaa over that of Baa while term spread is monthly spread of the yield of Treasury 10-year bond over the counterpart of 1-year bond. Loan size is the natural logarithm of the amount of money borrowed. Performance pricing is a dummy variable indicating the use of performance pricing in the loan. Regressors are scaled by 1/100. Standard errors are bootstrapped.

Panel A: Spread Regression

	size	M/B	leverage	profitability	tangibility
	-0.0735***	-0.0012	0.431***	-1.593***	0.134***
	credit spread	term spread	z	cash vol.	loan size
	0.0472	0.0345***	0.0235***	0.0000149	-0.110***
R-squared	loan purpose	loan type	credit rating	maturity	year&firm FE
0.86	Yes	Yes	Yes	Yes	Yes

Panel B: Connected bank vs. Spread Residual

	(1)	(2)
| spread residual |	7.334***	5.394***
	(1.383)	(1.751)
size	-7.293***	-4.799***
	(0.401)	(0.768)
M/B	-0.0899	0.129
	(0.526)	(1.233)
leverage	1.027	-3.127
	(4.133)	(4.064)
profitability		-44.28***
		(12.35)
tangibility		7.456
		(5.221)
credit spread		-2.804
		(6.272)
term spread		-2.469
		(1.684)
Z score		-0.373
		(0.909)
cash volatility		-0.00283
		(0.00495)
loan size		-2.395***
		(0.559)
N	7913	7913
Industry&Year FE	YES	YES
adj. R^2	0.135	0.162

Hypothesis 2.4.2. Given that a firm goes to a connected bank, the spread residual positively predicts the percentage share of capital in which the connected bank invests.

Based on this hypothesis, I run the following regression:

$$Skin = \beta_2 \times residual + controls$$

If these firms are transferred to connected banks to improve the matching efficiency when unobservable information is involved, then I should observe that a large spread residual (i.e., a negative shock) predicts a connected bank's high skin in the game, indicating its monitoring role, and therefore β_2 should be positive.

Table 2.2 presents the results of OLS regressions in which the dependent variable is the percentage allocation that a connected bank places in the syndicate, and the main independent variable is the spread residual. The regression results show that a bigger spread residual leads to a higher stake of a connected bank, which is consistent with the notion that a negative private shock migrates a firm to a connected bank for monitoring services.

Columns (3) and (4) rerun the tests with bank size included as a control to exclude the possibility of a mechanical relationship between a bank's size and its percentage allocation. The results show little difference. Note that it is not clear how bank size should be associated with bank allocation. For example, the relationship can be mechanically positive. Specifically, forming a syndicate for a given firm does not require as many large banks, which have more capital available than small ones, as small banks. That is, for a fixed investment need, large banks can fulfill the need more easily than small banks. However, it has been well documented that large banks tend to finance large firms while small banks grant loans to small companies. Given that large firms need more capital than small firms, large banks, which happen to have more capital, do not necessarily account for more allocation in their large firms than small banks put in their small firms. In fact, my theory seems to suggest that small banks are more likely to be specialized monitoring banks and thus to hold monitoring capital, as such scarce resources cannot all be held by large banks. Thus, small banks should have more skin in the game, consistent with a slightly negative correlation between bank size and bank allocation in the data. The results show that after bank monitoring and both observable and unobservable firm quality are taken care of, bank size turns out to show a positive relationship with skin in the game, which is consistent with the simple interpretation that controlling for my mechanism, a large bank can fill a large portion of a loan given the borrowing size and the borrower's size.

The loan spread-predicting regression uses the full sample of loans while any test with spread residual as an explanatory variable uses a subsample to which the corresponding research question is relevant. The use of more data in the first stage provides more power and thus greater precision for the tests in the second stage. More importantly, using the sub-sample of the second stage for both the first stage and the second stage tests, which is equivalent to a one-stage test using directly the loan spread and all control variables of the first stage, will produce a bias of self-selection. The subsample is a sample selected from that of the first stage for a particular reason and will yield inconsistent estimations in general. For example, the coefficients of the first stage using the full sample will differ from those of the sub-sample of all loans from connected banks, which estimate parameters as if the information about going to a connected bank is publicly observable ex-ante.

The test above investigates an unconditional relationship between a firm's negative private shock and its connected bank's skin in the game. However, if my story is accurate, then a conditional relationship should also hold; that is, a firm that receives an unfavorable shock should migrate to a connected bank that puts high skin in the game conditional on the skin in the game of the firm's last loan. Put differently, a negative shock should predict the connected bank's committing a higher stake than did the previous bank. In the model that has only two bank types, the conditional relationship and the unconditional relationship coincide: The firm with a negative private shock goes to a connected bank that is a monitoring type, and to a connected bank that has higher monitoring skills than the previous bank, which is a normal type. Two specifications can serve the purpose:

$$\Delta Skin = \beta_3 \times residual + controls$$

$$Skin = \beta_4 \times residual + LaggedSkin + controls$$

Δ Skin in the game is the percentage allocation from the connected bank subtracting lagged skin in the game, which is the percentage share that the previous

Table 2.2: Connected Bank Skin vs. Spread Residual-Unconditional.

This table presents the results of OLS regressions at the firm-connected-bank level where the dependent variable is the skin the connected bank has in the game, measured by its percentage allocation in which the bank puts. Columns (1) includes such firm-level controls as size, M/B and leverage, profitability and tangibility. Columns (2) also adds more controls including Altman's Z score, cash volatility, loan size, credit spread, term spread, performance pricing, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies and year fixed effects. All dummy variables are collapsed for brevity. Standard errors are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors are bootstrapped.

	(1)	(2)	(3)	(4)
spread residual	3.618**	4.742***	4.126**	5.663***
	(1.658)	(1.117)	(1.889)	(1.979)
size	-11.78***	-4.029***	-13.95***	-5.277***
	(0.917)	(0.759)	(0.902)	(1.352)
M/B	-2.326***	-0.969	-1.114	0.474
	(0.796)	(0.983)	(0.714)	(1.065)
leverage	-6.400	-3.414	-9.370	-4.569
	(5.815)	(3.735)	(7.420)	(4.637)
bksize			2.193***	3.102***
			(0.784)	(0.597)
profitability		-27.28**		-21.70
		(13.14)		(16.36)
tangibility		0.464		-0.584
		(5.063)		(6.649)
credit spread		-14.07		-13.14
		(9.120)		(8.551)
term spread		-3.819***		-6.365***
		(1.439)		(1.768)
Z score		0.222		0.465
		(0.437)		(0.310)
cash volatility		0.00101		0.00159
		(0.0114)		(0.0157)
loan size		-10.32***		-11.43***
		(0.653)		(2.120)
N	4327	4327	1618	1618
Industry&Year FE	YES	YES	YES	YES
adj. R^2	0.528	0.680	0.568	0.718

bank had put in prior to the loan of interest. The first specification tests whether a high residual can predict an increase in the skin in the game while the second examines whether a large residual leads to high skin conditional on the previous level of skin in the game. In any case, I expect both β_3 and β_4 to be positive. Table 2.3 presents the results. Coefficients of the spread residual are all significantly positive, suggesting that a negative private shock, proxied by a large spread residual, switches the firm to a connected bank that puts in more monitoring capital relative to the bank with which the firm has worked previously.

Implication 2.2.4 implies that although relationship banks sometimes help firms migrate to their connected banks, on average they are still associated with firms with better private shocks than connected banks are, based on which I build the following hypothesis,

Hypothesis 2.4.3. A large spread residual positively predicts a firm's probability of going to a connected bank against staying with its relationship bank.

I test this hypothesis with the following specification:

$$C = \beta_5 \times residual + controls.$$

To perform a cleaner test, I restrict the sample to those observations whose syndicate lead banks are either all connected banks or relationship banks, and therefore $C = 1$ indicates a connected bank while $C = 0$ refers to a relationship bank. A large spread residual corresponds to a bad shock and should be more associated with a connected bank than a small residual commensurate with a good shock is.

Columns (1) and (2) in Table 2.4 present the results of linear probability regressions, where Column (1) includes such firm-level controls as size, M/B and leverage, profitability, and tangibility and Column (2) also adds more controls, including Altman's Z score, cash volatility, loan size, credit spread, term spread, performance pricing, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies, and industry and year fixed effects. One can see that as the spread residual becomes greater, as compared to staying with the relationship bank, the firm has a higher chance of switching to a connected bank. Migration to a connected bank is always possible when the relationship bank can find a connected bank of the

Table 2.3: Connected Bank Skin vs. Spread Residual-Conditional.

This table presents the results of OLS regressions at the firm-connected-bank level where the dependent variable is Δ skin in the game in columns (1) and (2) and skin in the game for columns (3) and (4). Skin in the game measured by its percentage allocation in which the bank puts. Δ Skin in the game is the percentage allocation from the connected bank subtracting off lagged skin in the game and lagged skin in the game is the percentage share that the previous bank had put prior to the loan of interest. Columns (1) and (3) include such firm-level controls as size, M/B and leverage, profitability and tangibility. Columns (2) and (4) also add more controls including Altman's Z score, cash volatility, loan size, credit spread, term spread, performance pricing, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies and year fixed effects. All dummy variables are collapsed for brevity. Standard errors are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors are bootstrapped.

	Δ Skin in the game		Skin in the game	
	(1)	(2)	(3)	(4)
spread residual	5.397**	6.810***	3.504**	3.348**
	(2.740)	(2.464)	(1.721)	(1.566)
lagged skin in the game			0.195***	0.103**
			(0.0469)	(0.0406)
size	0.791	2.433*	-10.11***	-3.865***
	(0.897)	(1.371)	(1.065)	(1.066)
M/B	-2.923*	-1.910	-1.857**	-1.024
	(1.652)	(1.770)	(0.797)	(1.170)
leverage	0.159	0.554	-3.863	-3.020
	(10.64)	(11.56)	(7.135)	(5.388)
profitability		-28.96		-10.43
		(25.81)		(16.21)
tangibility		17.95		-0.775
		(13.11)		(5.151)
credit spread		-47.84***		-14.82*
		(15.66)		(8.883)
term spread		-5.600**		-4.834**
		(2.806)		(1.964)
Z score		-0.351		0.0123
		(2.064)		(0.942)
cash volatility		0.00380		0.00176
		(0.0177)		(0.00924)
loan size		-3.842***		-9.533***
		(1.134)		(0.754)
N	3147	3147	3147	3147
Industry&Year FE	YES	YES	YES	YES
adj. R^2	0.259	0.334	0.620	0.736

right type which has free capacity to take the referral. For example, if there is no capacity constraint and a monitoring bank is always connected to a normal bank, then the average quality of a loan granted by a relationship bank is no different than that by a connected bank, and we should observe insignificant coefficients in the first two columns. However, when a relationship bank cannot find an appropriate connected bank that is willing to accept the deal (i.e., it is not connected to a bank of a different type or the connected bank's capacity constraint is binding), some of the firms that need monitoring and nevertheless cannot find connected banks with monitoring skills will be inefficiently rationed by their relationship banks. This makes the average quality of a loan originated by a relationship bank higher than that by a connected bank. Columns (3) and (4) rerun the tests with the sub-sample where all syndicate lead banks are either connected banks or new banks, and the results show that as the spread residual increases, the probability of migrating to a connected bank decreases as compared to being left to the market.[11] This implies that firms that receive very negative shocks or are revealed to be very bad in quality will be abandoned to the market, and the market is rationally expecting that and charges them a very high interest rate.

2.5 Conclusion

This paper examines the impact of possible switching costs on the optimal firm-bank matching. Though the switching cost, as a result of informational frictions, impedes efficient migration from firms to banks, the private market seems to be relatively smart and able to generate some mechanism to reach quasi-first-best arrangements, as shown by the evidence that relationship banks tend to transfer deals that they find inappropriate to their connected banks, with which they have mutual trust and no commitment issues.

Although simplistic, the model should be able to be generalized into a dynamic generation overlapping model in which each firm lives for two periods and in each

[11]Notice that the result in Column (2) (Column (4)) is greater in magnitude as well as the t-statistic than that of Column (1) (Column (4)), indicating that the function of more controls here is simply to improve efficiency.

Table 2.4: Connected Bank vs. Spread Residual

This table presents the results of linear probability regressions with subsamples of data where the dependent variable is a dummy indicating whether the loan is from a connected bank. The first two columns include the sample of loans where all syndicate lead banks are either connected banks or relationship banks. The last two columns include the sample of loans where all syndicate lead banks are either connected banks or new banks. Columns (1) and (3) include such firm-level controls as size, M/B and leverage, profitability and tangibility. Columns (2) and (4) also add more controls including Altman's Z score, cash volatility, loan size, credit spread, term spread, performance pricing, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies, maturity dummies, loan purpose dummies, loan type dummies, credit rating dummies and year fixed effects. All dummy variables are collapsed for brevity. Standard errors are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors are bootstrapped.

	Connected or Relationship Bank		Connected or New Bank	
	(1)	(2)	(3)	(4)
spread residual	5.127***	5.653***	-4.511***	-4.909**
	(0.998)	(1.201)	(1.699)	(2.067)
size	-6.629***	-4.585***	4.128***	3.423***
	(0.473)	(0.954)	(1.082)	(1.054)
M/B	0.108	0.108	0.0671	0.511
	(1.136)	(1.363)	(1.808)	(1.253)
leverage	-4.040	-3.988	-0.944	-1.448
	(3.192)	(3.603)	(5.352)	(5.245)
profitability	-43.21***	-40.46***	-0.218	-6.974
	(11.59)	(13.37)	(16.70)	(16.46)
tangibility	7.103	7.108	-1.203	0.390
	(6.368)	(6.247)	(7.013)	(8.993)
credit spread		-4.175		13.34
		(6.479)		(13.37)
term spread		-2.161		-1.936
		(1.531)		(2.538)
Z Score		-0.665		0.292
		(0.557)		(1.098)
cash volatility		-0.00285		-0.0236
		(0.00634)		(0.0320)
loan size		-2.819***		1.255
		(0.606)		(0.907)
N	8754	8754	1947	1947
Industry&Year FE	YES	YES	YES	YES
adj. R^2	0.151	0.176	0.291	0.300

period old firms and young firms coexist. Specifically, in each period, a number of young firms enter the market with a type unknown to all banks and a pooling equilibrium exists such that the pool financed by normal banks or monitoring banks includes all three types of firms and the expected quality of the monitored (normal) pool is closer to the medium (good) quality than that of the normal (monitored) pool. In the next period, those young firms become old and get a second round of financing, and a new batch of young firms enters the market and fulfils the remaining lending capacity of banks that have no firm in hand. Although I conjecture that the main implications of the static setting should not change, the dynamic version may generate more insights as well as subtle implications that can explain more borrowing behavior in the data.

Chapter 3

Firm Links and Merger Propagation: Evidence from Corporate Alliances

3.1 Introduction

An important research agenda in finance concerns the determinants of merger activity, and in particular why mergers seem to occur in waves (e.g., Andrade, Mitchell, and Stafford, 2001; Shleifer and Vishny, 2003). A subset of the literature explains this phenomenon from the perspective of merger propagation. For example, a rival's expansion through merger and acquisition (M&A) generates a need for other firms in the same industry to catch up in which case the force of countervailing competitors' market power leads to merger clustering within an industry (Harford, 2005); the consolidation of an upstream industry through M&A creates an incentive for its downstream industry to consolidate in which case inter-industry links facilitate merger propagation across industries (Ahern and Harford, 2014). More recently, Harford et al. (2014) also emphasize the important role of inter-firm links in explaining merger activity by showing a higher likelihood of merger between firms that have a customer-supplier relationship. Therefore, it is interesting to investigate whether an inter-firm link leads to merger propagation as well; specifically, given that two firms have an economic link, will one firm's merger with a third firm (instead of its connected partner as in Harford, Schonlau, and Stanfield, 2014) also increase its partner's probability of engaging in M&A?

In this paper, I address this question by proposing a micro-founded channel through which a firm's merger event can propagate to another firm with which the first firm has formed a corporate alliance. Strategic alliances bring together otherwise disparate organizations to share resources and are important economic links usually associated with a favorable stock price response (Chan et al., 1997). I argue that a firm's merger generates significant resource reallocation within its alliance and can potentially cause its partner to engage in M&A as well. For example, if a firm loses its partner's key complementary resources after the partner is merged, the firm may look for a new partner by engaging in M&A; on the other hand, more complementary resources may be made available via a partner's merger and therefore improve the productivity of the first firm, which then may want to expand through mergers.[1] These conjectures are not without theoretical support; by modeling an economy where business units bilaterally exchange resources, Anjos (2011) shows that alliance networks can be associated with merger propagation via strategic complementarities of merger decisions. I show that the proposed mechanism's key predictions are consistent with US data on inter-corporate alliances and mergers. My results, which emphasize firm-level connections—in contrast to the sectoral links in Ahern and Harford (2014)—are robust to controlling for many other factors that might make the association between mergers and alliances spurious. In particular, I show that my results are not driven by time-varying merger activity occurring at the industry level.

Specifically, I verify the mechanism's main implications using data on US corporate alliances and mergers for the period 1990-2011. In my main empirical analysis, I test whether the likelihood that a given firm engages in M&A is associated with previous M&A activity by its alliance partners. I find that this association is present and is statistically and economically significant, with an increase in merger likelihood on the order of 13%-38% versus unconditional probabilities. The association between partner merger and own M&A activity is stronger for partner mergers taking place with a lag of one year; but is also present with a lag of two years. This suggests that resource-reallocation externalities may on occasion take some time to operate. On the other hand, that results are obtained with a lag of two years makes it more plausible that partner mergers are reasonably exogenous to own restructuring decisions. My results are robust to the inclusion of company characteristics, industry-year fixed effects (for various industry classifications), and even firm fixed effects. The latter control for the possibility that unobserved factors may make some firms more prone to merger activity, while also making it more likely that these firms establish alliances among themselves. This type of clustering is consistent with observed alliance behavior such as assortative matching (Anjos and Drexler, 2015).

[1] The first example shows the case of negative externalities in which the affected firm has a lower marginal cost of being merged while the second scenario demonstrates positive externalities which raise a partner firm's marginal benefit in a new merger.

As a second empirical analysis, I follow the mechanism's implication that resource reallocation is at the heart of the externality mechanism that triggers an additional merger. I develop proxies for the strength of post-merger resource reallocation and then test whether the propagation effect is explained by these proxies. My main proxy is in the spirit of the Q-theory of mergers in Jovanovic and Rousseau (2002), where mergers are simply reallocation of capital from low-productivity—and hence low Q—firms to more productive organizations.[2] For each partner merger, I thus compute the ratio between the Tobin's Q of the partner's M&A counterpart and the Tobin's Q of the partner itself as a proxy for the magnitude of reallocation. I find that high-Q-ratio partner mergers are indeed more likely to generate merger propagation. The other proxies I use for the strength of reallocation are the ratio of firm size, difference in profitability, and finally whether the partner firm took on the role of target in the merger. With all these proxies I find that the propagation effect is stronger.

I conduct two additional empirical investigations. First, and building on the intuition that resource reallocation is the externality mechanism leading to the M&A response, I conjecture that these effects can operate at a distance. What I mean by distance is that a particular merger may lead to a cascade of resource reallocation via the inter-firm alliance network, as opposed to only having localized effects. I test this hypothesis by constructing a variable—which I term *merger centrality*—that quantifies a firm's average proximity to economy-wide M&A activity, within the context of the alliance network. As expected, I find that high-merger-centrality firms are more likely to engage in M&A activity. Second, and also in the spirit of my main argument, I hypothesize that a firm's response to a partner-merger shock might take the form of building new alliances, in those instances where M&A is costly. Consistent with this hypothesis, I find that partner mergers are also associated with a higher likelihood of new alliance formation. Although this finding is more focused on alliance behavior, it is also relevant for merger propagation because the creation of new links creates further possibilities for link-driven diffusion of merger activity.

To further validate my main hypothesis, I conduct additional tests to resolve other endogeneity concerns. For example, one may argue that my results can be explained by an alternative story that it is the failure of an alliance instead of strategic

[2]The economic magnitude associated with this mechanism was, however, challenged in Rhodes-Kropf and Robinson (2008).

complementarity that leads each alliance member to look for a new partner through M&A. To disentangle this potential confounding effect from my results, I construct two variables to proxy for alliance performance by computing the average change in alliance member profitability and stock return since the start of the alliance and redo my main test with these variables included as controls. Alternatively, I drop observations with bad alliance performance based on the constructed variables and check whether my main result still holds with this sample. Both the tests yield similar results, implying that my observations are unlikely to be driven by a potential correlation between omitted alliance performance and member merger activity. Next, I employ the instrument variable (IV) approach to further exclude the possibility of mis-interpretation from mere perverse correlations. Specifically, I use the firm partner's industry merger waves as an instrument for the merger activity of its partner and claim that firm-level unobservables, such as alliance performance, should not be correlated with the partner's industry-level shocks. The resulting two-stage least squares (2SLS) regressions show qualitatively similar results, indicating that my results are robust to the potential existence of firm heterogeneity that is correlated with my variable of interest. Finally, I perform several other robustness checks of my main test and find mostly similar results.

The paper is mainly related to three strands of literature. First, I consider a micro-founded channel for a single merger event to propagate across alliance links, offering a new angle to explain merger clustering and contributing to the literature on merger waves and contagion (e.g., Gorton, Kahl, and Rosen, 2009; Goel and Thakor, 2010). In addition, the study is also generally related to the literature regarding shock transmission (e.g., Cohen and Frazzini, 2008; Acemoglu et al., 2012) in that I investigate whether one partner's merger activity within an alliance creates externalities to the other party and how the affected party responds to these shocks. Finally, the paper finds a new function of strategic alliances, which is to work as a channel for merger propagation, and adds to the alliance literature (e.g., Robinson and Stuart, 2007; Ozmel, Robinson, and Stuart, 2007).

The remainder of the paper is organized as follows. Section 3.2 explains the data and sample construction which I use for my later empirical analysis. Section 3.3 tests the main implications of the mechanism that I propose. Section 3.4 contains additional empirical analyses and robustness checks of the main results, and Section 3.5 concludes.

3.2 Data and Sample Construction

This section explores US data on corporate alliances and mergers to test the two key hypotheses that follow from my proposed mechanism that mergers propagate through alliances. The first is whether firms are more likely to engage in M&A activity when their partners have done so in the past (section 3.3). The second tests the mechanism I propose more directly: I ask specifically whether the strength of post-partner-merger resource reallocation generates stronger propagation effects (section 3.3.3).

I collect my data from four sources: Security Data Company's (SDC's) Mergers & Acquisitions Database and Strategic Alliances (SA) Database, Compustat, and CRSP. I use the sample of all U.S. firms from Compustat and construct a firm-year panel containing information on each firm's SA partners and each firm's M&A counterpart. A key limitation of the alliance data is that SDC usually only provides information about the starting date for each alliance, and not about the duration or termination of the partnership (for only 3% of cases do I have expected duration). In my main specifications, I assume that alliances are never terminated. To address concerns that this biases my results, I conduct robustness checks in which I run specifications using alternative assumptions, specifically, that alliances last for 5 years or 10 years (see section 3.4.4).

The first step in constructing my panel is to obtain all SA instances from SDC where all corporate participants are located in the US. This results in a firm-year-partner panel of more than one million observations, which I then merge with SDC's M&A Database to determine if and when a firm and its partner(s) are involved in an M&A event. I next collapse this dataset into a more parsimonious firm-year panel, such that in each year, I know whether a firm engages in M&A and also whether any of its SA partners engages in M&A. At this stage, I am left with slightly more than 46,000 observations.

Finally, I merge the panel including all U.S. firms with the whole Compustat sample, which leads to more than half of the SA firm sample being dropped. This is not surprising, since SDC's Strategic Alliance Database includes many private firms. With this panel, for any Compustat firm in any year, I know whether it has an alliance partner (public or private) and the M&A status of both its partners and itself. For the purpose of my multivariate analysis, I supplement the panel with firm characteristics constructed from Compustat and CRSP. Following mainstream

Table 3.1: Summary Statistics.

The table presents means, standard deviations (SD), percentiles, and the number of observations for each variable. MA is a dummy variable (for public firms) taking the value of one if the firm is involved in an M&A transaction, $PART$ indicates whether the firm has at least one partner (public or private), PMA_1 is a dummy variable capturing whether one of the firm's partners engaged in M&A during the previous year (zero also if there are no partners), ROA is return on operating assets (ratio of operating income before interest, taxes, and depreciation over total book assets), $SIZE$ is the log of total book assets, LEV is the ratio of total debt over the sum of debt and common equity, MTB is the ratio of equity market capitalization over book equity, $SGROWTH$ denotes sales growth, AGE counts the number of years since the firm first shows up in Compustat, $QRATIO$ is the ratio between the Tobin's Q of a partner-firm's M&A counterpart and the Tobin's Q of the partner itself, $SRATIO$ is the ratio between the log size of a partner-firm's M&A counterpart and the log size of the partner itself, $ROADIF$ is the difference between the ROA of a partner-firm's M&A counterpart and the ROA of the partner itself, TGT is a dummy taking the value of one if a partner firm was engaged in M&A in the role of target, AL is a dummy variable (for public firms) taking the value of one if the firm is involved in an alliance, CEN is an eigenvector-like centrality measure quantifying a firm's proximity to economy-wide M&A activity (following the concept of alpha-centrality in Bonacich and Lloyd, 2001, with α set to three different levels, and under assumption of 5-year alliances), and $DEGREE$ counts a firm's number of partners (under assumption of 5-year alliances). Observations for CEN are conditional on the firm having at least one alliance link.

	Obs.	mean	SD	p5	p50	p95
MA	75994	0.202	N.A.	N.A.	N.A.	N.A.
$PART$	75994	0.231	N.A.	N.A.	N.A.	N.A.
PMA_1	75994	0.114	N.A.	N.A.	N.A.	N.A.
ROA	75994	0.075	0.183	-0.262	0.110	0.261
$SIZE$	75994	5.310	2.333	1.732	5.147	9.446
LEV	75994	0.365	0.246	0.014	0.349	0.812
MTB	75994	3.532	7.755	0.505	1.903	9.723
$SGROWTH$	75994	0.356	1.884	-0.280	0.099	1.130
AGE	75994	15.481	15.488	1	11	47
$QRATIO$	3640	3.237	10.120	0.177	1.063	10.223
$SRATIO$	4428	-1.570	3.541	-6.952	-1.838	5.103
$ROADIF$	4247	0.104	3.906	-0.613	-0.009	0.628
TGT	8652	0.411	N.A.	N.A.	N.A.	N.A.
AL	75994	0.053	N.A.	N.A.	N.A.	N.A.
$CEN(\alpha = 0.1)$	13373	0.0076	0.020	0	0.0034	0.0283
$CEN(\alpha = 0.5)$	13373	0.058	0.168	0	0.0182	0.228
$CEN(\alpha = 0.9)$	13373	0.395	1.446	0	0.0411	1.735
$DEGREE$	70922	0.819	5.989	0	0	4

Table 3.2: M&A and Firm Characteristics.

The table shows the difference in averages for various firm characteristics across two subsample: firms that engage in M&A and firms that do not. Statistical significance of t tests for difference in means is indicated at the 10% level by *, at the 5% level by **, and at the 1% level by ***. Description of firm characteristics is presented in table 3.1.

	$MA = 1$	$MA = 0$	Difference
$PART$	0.399	0.188	0.211***
ROA	0.117	0.065	0.0523***
$SIZE$	5.914	5.157	0.757***
LEV	0.352	0.369	-0.0167***
MTB	3.594	3.516	0.0780
$SGROWTH$	0.342	0.359	-0.0177
AGE	18.523	14.710	3.813***
$CEN(\alpha = 0.5)$	0.030	0.005	0.0251***
$DEGREE$	2.467	0.426	2.041***

finance literature on mergers, I drop financial and utility firms, which leaves me with a final sample of around 75,000 observations. Summary statistics are presented in Table 3.1. Differences across the two key sub-samples of firms—the ones that engage in M&A and the ones that do not—are shown in Table 3.2.

Table 3.2 shows that firms engaging in M&A systematically differ from those that do not. For example, firms that engage in M&A are more likely to have partners, are more profitable, and are bigger. The systematic differences in firm characteristics across the sub-samples suggest that one must be careful about endogeneity concerns since it is reasonable to conjecture that the subsamples also vary with respect to unobservable characteristics. To address this concern, much of the empirical analysis controls for fixed effects at the industry, industry-year, and firm level.

3.3 Results

3.3.1 Does partner M&A activity make M&A more likely?

In a first analysis of my data, I employ a simple procedure to understand whether alliance links make mergers more likely. For every pair of public firms in my sample that is involved in an alliance in the previous year, and where only one of the firms engages in merger activity, I construct a matching pseudo pair with similar characteristics. More specifically, I identify pairs of firms that do not have an alliance, but belong to the same SIC3 industry. For the firm engaged in M&A—denoted as firm 1— I identify a matched firm in the same industry that also engaged in M&A in the same period. When several matches are identified, I choose firms based on size and Tobin's Q similarity.[3] I conduct the same procedure for the firm in the real pair that did not engage in M&A—denoted as firm 2. Given the matching procedure, I control, albeit imperfectly, for some observable firm characteristics and industry-year fixed effects. My expectation, in light of the propagation argument developed above, is that firm 2 in the real pairs is more likely to engage in M&A than firm 2 in the pseudo pairs. Figure 3.1 plots the merger frequency for each type of pair, for the period 1990-2011.

[3] More specifically, I match by picking the firm with the most similar Tobin's Q of all the firms within a 10% radius in asset size.

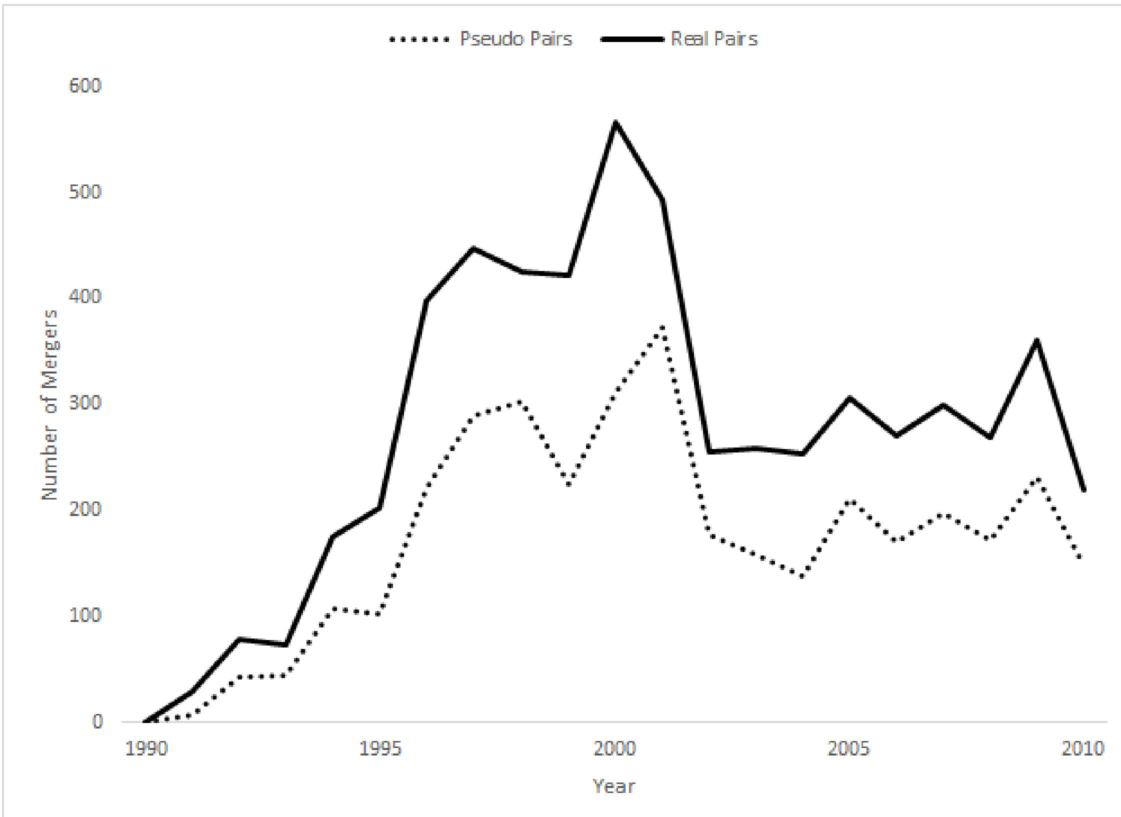

Figure 3.1: Alliances and Mergers – Matching Approach.
The picture shows the number of mergers for firms in real pairs and firms in pseudo pairs. Real pairs correspond to two firms that have an alliance in the past year, and where one of the partners engaged in M&A in that period. Pseudo pairs also involve two firms where one engaged in M&A last year, but where an alliance does not exist. For each real pair I identified a pseudo pair by matching on industry, size, and Tobin's Q.

Figure 3.1 confirms my expectation: for every year, real pairs experience more merger clustering than pseudo pairs. The figure is illustrative but naturally limited in terms of the robustness of the inference procedure. For example, the analysis does not take into account that firms engaging in M&A more intensely might also engage in alliances. Furthermore, I am controlling only for a few firm characteristics and not addressing potential endogeneity concerns associated with unobserved heterogeneity. To deal with these issues in testing the propagation effect, my main econometric analysis employs the linear probability model in equation (3.1).

$$\Pr\{MA_{i,t} = 1\} = \beta_0 + \sum_{n\in\{1,2\}} \beta_{1,n} \times PMA_{i,t-n} + \beta_2 \times PART_{i,t} + CTRLS_{i,t-1} \quad (3.1)$$

In equation 3.1, $MA_{i,t}$ is equal to one if firm i merges in year t and zero otherwise, $PMA_{i,t-n}$ is a dummy variable indicating whether in year t firm i has a partner merged in year $t-n$, where $n \in 1,2$, and $PART_{i,t}$ is one if the firm has at least one partner in year t and zero otherwise.[4] To avoid the issue of simultaneity, all right-hand-side control variables are lagged (except for the control variable age). For the main explanatory variables, I consider events in the past two years since I do not know *a priori* how long it would take for the shock to have an effect. A somewhat lagged response to the shock seems reasonable because (i) resource reallocation may take some time to occur and (ii) being matched with a suitable M&A partner also takes time. I expect the coefficients $\beta_{1,n}$ to be positive.

Table 3.3 presents the estimation results of equation (3.1). Control variables include lagged return on assets (ROA), size, leverage, market-to-book ratio, sales growth, and age. Industry-year fixed effects employ 3-digit SIC codes. A finer level classification would perhaps capture industry effects more adequately but, on the other hand, could be more subject to misclassification. All standard errors are clustered at the firm level.

The first column in Table 3.3 is a simple regression where I only include my key variables as regressors, along with year fixed effects, since as we know mergers occur

[4]Note that under my assumption alliances last forever, $PART_{i,t} = 1$ implies $PART_{i,t+\tau} = 1$ for all τ. Therefore, an appropriate interpretation of $PART_{i,t} = 1$ is that firm i entered into an alliance at least once at t or some previous time period.

Table 3.3: Partner M&A Activity and the Likelihood of Merging.

This table shows OLS regressions where the dependent variable is $MA_{i,t}$, a dummy taking the value of one if firm i is engaged in merger activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, and PMA, which indicates whether the firms' partners were involved in a merger deal in the past. The subscript on PMA indicates the lag in years. t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)
PMA_1	0.0770***	0.0645***	0.0668***	0.0276***	0.0256**
	(0.00937)	(0.00902)	(0.00917)	(0.00991)	(0.0109)
PMA_2	0.0427***	0.0293***	0.0274***	0.00189	-0.00234
	(0.00937)	(0.00903)	(0.00914)	(0.00969)	(0.0106)
$PART$	0.140***	0.139***	0.137***	0.0319***	0.0337***
	(0.00809)	(0.00785)	(0.00791)	(0.0114)	(0.0123)
ROA		0.213***	0.177***	0.108***	0.106***
		(0.00979)	(0.0106)	(0.0120)	(0.0142)
$SIZE$		0.0116***	0.0178***	0.0179***	0.0144***
		(0.00135)	(0.00153)	(0.00334)	(0.00387)
$BLEV$		-0.0520***	-0.0602***	-0.177***	-0.172***
		(0.00865)	(0.00898)	(0.0107)	(0.0120)
MTB		0.00125***	0.00136***	0.00210***	0.00202***
		(0.000211)	(0.000218)	(0.000232)	(0.000267)
$SGROWTH$		0.00308***	0.00244***	0.000406	0.000143
		(0.000703)	(0.000743)	(0.000756)	(0.000879)
AGE		0.000608***	0.000777***	-0.000764	-0.136
		(0.000198)	(0.000206)	(0.00389)	(1.831)
N	75994	75994	75994	75994	75994
R^2	0.051	0.069	0.168	0.365	0.430
Year FE	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	No	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes

in waves. The results show a statistically significant positive association between mergers involving the firm's partners and the likelihood that the firm engages in mergers. The effect is also economically significant: If a firm's partner engages in M&A in the previous year, there is an additional 7.7% likelihood that the firm will merge in the current period. This represents an increase of 38% relative to the unconditional merger probability. Model (1) also shows that the effect is strongest for more recent shocks but still sizable for two-year lags. The advantage of using two year lags is that the partner merger is more likely to be exogenous to the firm's own M&A choices.

Specifications (2)-(4) add control variables and industry-year fixed effects, and the results do not change significantly. The inclusion of industry-year fixed effects is particularly important because it allows me to conclude that the additional merger likelihood is not due to a common factor that affects all firms in a given industry at that point in time. Such effects should be expected given previous research on merger waves and merger propagation (Mitchell and Mulherin, 1996; Andrade, Mitchell, and Stafford, 2001; Ahern and Harford, 2014). The caveat is that the quality of my industry-year fixed effect critically hinges on industry classification. Later I conduct a robustness check that partially addresses this concern.

Models (4) and (5) include firm fixed effects. One reason to include firm fixed effects is concern about omitted variables. For example, firms with an unspecified characteristic may be more likely to engage in M&A and simultaneously partner with one another. This conjecture seems reasonable in light of the assortative-matching patterns in alliances (Anjos and Drexler, 2015). The drawback of using firm fixed effects is that the regression focuses on serial acquirers, the type of firms for which I have time-series variation in merger activity; arguably, my story is less about these firms and more about the cross section. In specifications (4) and (5) I still find the propagation effect, at least for a lag of one year, but the economic magnitude of the effect is more than halved. In model (5) the effect of partner mergers corresponds to an additional 13% likelihood of engaging in M&A activity versus the unconditional probability.

3.3.2 Industry definitions – robustness check

The above analysis may give rise to concern that I do not control for industry classification at a fine enough level. If that is the case, unobserved time variation at the industry level might be driving my results. Although one can never fully address this issue, this section presents evidence to indicate this is not a problem.

Table 3.4 estimates the same model for the likelihood of merging as Table 3.3 (in particular, specification (3)), but I use alternative industry definitions to capture industry-year fixed effects. Model (1) employs a coarser classification, the 2-digit SIC code level. Model (2) shows my original model, where industries are classified at the 3-digit level. Model (3) employs the SIC classification at the lowest possible level, the 4-digit SIC code. Model (4) imposes an even finer industry classification, with 6-digit NAICS codes. Finally, model (5) in Table 3.4 employs the Fama-French industry classification.

As expected, when I increase the level of detail in industry classification much more of the variation in M&A in the panel is absorbed by industry-year fixed effects. However, comparing the coefficients of interest across models, I note that the effect of partner M&A activity is essentially the same. Moreover, if the concern that I am not controlling for industry effects at a sufficiently detailed level is valid, then one would expect the main coefficients to become stronger under the 2-digit SIC specification, relative to the 3-digit SIC specification, which is not the case.

3.3.3 Resource reallocation and the strength of the propagation effect

The mechanism's main prediction relies on an externality caused by resource reallocation after a merger. If this occurs in data, then instances when I would observe more resource reallocation should be associated with a higher propagation effect. I test this second hypothesis by constructing what I believe are reasonable proxies for the strength of resource reallocation. My main proxy is the ratio between the Tobin's Q of the partner's M&A counterpart and the Tobin's Q of the partner itself. A higher asymmetry in the Tobin's Q would be associated with a higher reallocation of resources from the low-Q firm to the high-Q firm, a rationale consistent with the neoclassical Q-theory of mergers (Jovanovic and Rousseau, 2002). Equation 3.2 is the linear probability model I use to test this hypothesis:

Table 3.4: Controlling for Industry-Year FE Using Alternative Industry Definitions.

This table shows OLS regressions where the dependent variable is $MA_{i,t}$, a dummy taking the value of one is firm i is engaged in merger activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, and PMA, which indicates whether the firms' partners were involved in a merger deal in the past. The subscript on PMA indicates the lag in years. t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)
PMA_1	0.0630***	0.0668***	0.0670***	0.0614***	0.0642***
	(0.00892)	(0.00917)	(0.00945)	(0.0103)	(0.00896)
PMA_2	0.0280***	0.0274***	0.0268***	0.0282***	0.0282***
	(0.00901)	(0.00914)	(0.00935)	(0.0103)	(0.00897)
$PART$	0.135***	0.137***	0.141***	0.146***	0.137***
	(0.00771)	(0.00791)	(0.00802)	(0.00875)	(0.00775)
ROA	0.193***	0.177***	0.172***	0.169***	0.190***
	(0.0102)	(0.0106)	(0.0109)	(0.0118)	(0.0103)
$SIZE$	0.0155***	0.0178***	0.0175***	0.0174***	0.0147***
	(0.00146)	(0.00153)	(0.00154)	(0.00168)	(0.00143)
$BLEV$	-0.0586***	-0.0602***	-0.0640***	-0.0612***	-0.0571***
	(0.00875)	(0.00898)	(0.00920)	(0.0101)	(0.00882)
MTB	0.00128***	0.00136***	0.00139***	0.00140***	0.00127***
	(0.000210)	(0.000218)	(0.000222)	(0.000244)	(0.000210)
$SGROWTH$	0.00294***	0.00244***	0.00226***	0.00209**	0.00310***
	(0.000708)	(0.000743)	(0.000775)	(0.000860)	(0.000707)
AGE	0.000941***	0.000777***	0.000773***	0.000800***	0.000713***
	(0.000201)	(0.000206)	(0.000207)	(0.000228)	(0.000202)
N	75994	75994	75994	75994	75994
R^2	0.106	0.168	0.212	0.311	0.098
SIC2 x Year FE	Yes	No	No	No	No
SIC3 x Year FE	No	Yes	No	No	No
SIC4 x Year FE	No	No	Yes	No	No
NAICS x Year FE	No	No	No	Yes	No
FF49 x Year FE	No	No	No	No	Yes

$$
\begin{aligned}
\Pr\{MA_{i,t}=1\} \;=\;& \beta_0 + \sum_{n\in\{1,2\}} \beta_{1,n}\times PMA_{i,t-n} + \beta_2 \times PART_{i,t} + \\
& + \sum_{n\in\{1,2\}} \beta_{3,n}\times PMA_{i,t-n}\times QRATIO_{i,t-n} + CTRLS_{i,t-1}
\end{aligned} \tag{3.2}
$$

The new term $QRATIO$ in the equation captures the asymmetry between merging firms so I expect the coefficients $\beta_{3,n}$ to be positive. For a firm that has more than one partner merged in the same year, I take the highest value of this variable. As before, the empirical model includes control variables, specifically, ROA, size, leverage, market-to-book ratio, sales growth and age, all of which are one-year lagged except for age. The results are presented in Table 3.5.

As expected, coefficients on the term $PMA \times QRATIO$ are positive and statistically significant, and this is true across specifications. The effect is also economically significant. Take, for example, specification (3) in Table 3.5, where the PMA_1 coefficient is 0.068 and the $PMA_1 \times QRATIO$ coefficient is 0.003. Given the standard deviation in the $QRATIO$ variable, about 10, a one-standard-deviation increase in this variable corresponds to an additional 3% likelihood that the firm will engage in M&A. This is more than a 40% increase over the baseline effect and corresponds to a 15% increase relative to the unconditional M&A probability.

As a robustness check of the above result, I consider three alternative proxies for the resource reallocation effect. First, I use the difference in profitabilities,[5] which is an alternative to Q for measuring the asymmetry in the investment opportunity set across firms. Second, I compute the ratio in firm size. Here the rationale is that if the partner's M&A counterpart is larger than the partner itself, then that partner's resources are more likely to be absorbed by projects in the large organization. Third, I use a dummy where the partner takes on the role of target in the acquisition. My conjecture is a firm is more likely to be acquired for its resources when it takes on the more passive role of target. In occasional cases when the firm has more than one partner being merged in the same year, I use the role of the partner whose M&A occurred most recently. The results are summarized in Table 3.6, which replicates specification (3) from Table 3.5, but using the alternative resource-allocation proxies.

[5] Given that profitabilities can be negative, ratios would give inconsistent rankings.

Table 3.5: Propagation Effect and Asymmetries in Merging Firms – Q Ratio.

This table shows OLS regressions where the dependent variable is $MA_{i,t}$, a dummy taking the value of one if firm i is engaged in merger activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, PMA, which indicates whether the firms' partners were involved in a merger deal in the past, and $QRATIO$, the ratio of Tobin's Q between the firm's partner merger counterpart and the firm's partner (for multiple events I take the maximum). The subscript on PMA indicate the lag in years. t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)
PMA_1	0.0749***	0.0618***	0.0684***	0.00840	0.00577
	(0.0190)	(0.0186)	(0.0186)	(0.0224)	(0.0245)
PMA_2	0.0760***	0.0660***	0.0584***	0.0295	0.0160
	(0.0189)	(0.0186)	(0.0187)	(0.0212)	(0.0233)
$PMA_1 \times QRATIO$	0.00301***	0.00258***	0.00299***	0.000760	0.00110
	(0.000816)	(0.000776)	(0.000780)	(0.000713)	(0.000803)
$PMA_2 \times QRATIO$	0.00476***	0.00421***	0.00414***	0.00208**	0.00222**
	(0.000858)	(0.000809)	(0.000764)	(0.000908)	(0.000898)
$PART$	0.140***	0.139***	0.137***	0.0136	0.0188
	(0.00827)	(0.00808)	(0.00813)	(0.0123)	(0.0133)
ROA		0.208***	0.166***	0.0912***	0.0843***
		(0.0100)	(0.0108)	(0.0121)	(0.0145)
$SIZE$		0.00777***	0.0142***	0.0162***	0.0131***
		(0.00134)	(0.00153)	(0.00340)	(0.00400)
$BLEV$		-0.0387***	-0.0486***	-0.162***	-0.158***
		(0.00877)	(0.00920)	(0.0109)	(0.0124)
MTB		0.00107***	0.00115***	0.00188***	0.00180***
		(0.000214)	(0.000221)	(0.000232)	(0.000271)
$SGROWTH$		0.00292***	0.00225***	0.000486	0.000279
		(0.000711)	(0.000756)	(0.000771)	(0.000901)
AGE		0.000572***	0.000607***	-0.000359	-0.129
		(0.000207)	(0.000217)	(0.00427)	(3.524)
N	68352	68352	68352	68352	68352
R^2	0.037	0.052	0.160	0.380	0.451
Year FE	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	No	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes

Table 3.6: Propagation Effect and Asymmetries in Merging Firms – Alternative Proxies.

This table shows OLS regressions where the dependent variable is $MA_{i,t}$, a dummy taking the value of one if firm i is engaged in merger activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, PMA, which indicates whether the firms' partners were involved in a merger deal in the past, and LR (stands for "Large Reallocation"), which is a proxy for the strength of post-partner-merger resource reallocation. There are three alternative variables for this proxy: $ROADIF$, which measures difference in ROA, $SRATIO$ is the size ratio, and TGT is a dummy equal to one if the partner was a target in the merger. The subscripts on PMA indicate the lag in years. t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	$LR = ROADIF$		$LR = SRATIO$		$LR = TGT$	
	(1)	(2)	(3)	(4)	(5)	(6)
PMA_1	0.0732***	-0.00252	0.104***	0.0121	0.0401***	0.0132
	(0.0161)	(0.0205)	(0.0161)	(0.0203)	(0.00980)	(0.0118)
PMA_2	0.0699***	0.0271	0.0801***	0.0233	0.00702	-0.00640
	(0.0164)	(0.0196)	(0.0159)	(0.0194)	(0.00999)	(0.0117)
$PMA_1 \times LR$	0.00510***	0.00205*	0.0150***	0.00557*	0.0691***	0.0340***
	(0.000769)	(0.00123)	(0.00264)	(0.00323)	(0.0113)	(0.0122)
$PMA_2 \times LR$	0.000594	-0.00220	0.0142***	0.00354	0.0482***	0.0110
	(0.00183)	(0.00214)	(0.00277)	(0.00332)	(0.0118)	(0.0126)
$PART$	0.136***	0.0198	0.136***	0.0200	0.137***	0.0339***
	(0.00812)	(0.0132)	(0.00809)	(0.0131)	(0.00790)	(0.0123)
ROA	0.168***	0.0868***	0.167***	0.0891***	0.176***	0.106***
	(0.0108)	(0.0145)	(0.0107)	(0.0145)	(0.0106)	(0.0142)
$SIZE$	0.0147***	0.0129***	0.0141***	0.0134***	0.0171***	0.0143***
	(0.00154)	(0.00399)	(0.00152)	(0.00398)	(0.00151)	(0.00386)
$BLEV$	-0.0496***	-0.160***	-0.0502***	-0.160***	-0.0595***	-0.171***
	(0.00920)	(0.0123)	(0.00914)	(0.0123)	(0.00896)	(0.0120)
MTB	0.00119***	0.00184***	0.00118***	0.00186***	0.00133***	0.00201***
	(0.000221)	(0.000269)	(0.000219)	(0.000268)	(0.000217)	(0.000267)
$SGROWTH$	0.00227***	0.000325	0.00226***	0.000292	0.00243***	0.000154
	(0.000756)	(0.000893)	(0.000755)	(0.000892)	(0.000742)	(0.000879)
AGE	0.000661***	-0.180	0.000594***	-0.202	0.000726***	-0.139
	(0.000217)	(3.384)	(0.000212)	(3.410)	(0.000203)	(1.838)
N	69082	69082	69327	69327	75994	75994
R^2	0.161	0.450	0.163	0.450	0.169	0.430
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Table 3.6 shows that the effect is robust across specifications. Merger propagation is more likely with higher values of the post-partner-merger resource allocation proxies. The results are not only statistically significant, but also economically meaningful. Considering the interaction effect with a lag of one year and the specification without firm fixed effects, a one-standard-deviation increase in profitability difference is associated with an additional 2% (0.005 x 3.9) merger likelihood. The same effect is stronger with the size ratio proxy, with an additional 5% (0.015 x 3.5) merger likelihood. The effect with the target dummy is the strongest, with an additional M&A probability of 6.9%, which is even greater than the baseline likelihood of 0.04 in that model.

It is also interesting to note that for those specifications in Table 3.6 with firm fixed effects, the propagation effect that survives (statistically) is the one where I interact the merger event with the resource reallocation proxies.

3.4 Additional empirical analyses

This section contains two additional analyses that are close to the mechanism postulated for the main tests, discusses further endogeneity tests, and presents a summary of the robustness checks I conduct.

3.4.1 A network approach

Furthermore, it seems natural to conjecture that post-merger reallocation shocks may be operating at greater distances. That is, a merger could generate externalities throughout the network of alliances, instead of having just a localized effect. Following this logic, I construct a variable that detects how close a particular firm is to economy-wide M&A activity, where distance is defined within the context of the alliance network. My variable is borrowed from the social networks literature (Bonacich and Lloyd, 2001), and is a natural extension of eigenvector centrality. For a symmetric adjacency matrix A with typical element a_{ij}, the simple measure of eigenvector centrality for node i, denoted by x_i, is defined as

$$x_i = \frac{1}{\lambda}\left[a_{1i}x_1 + a_{2i}x_2 + ...\right] \Leftrightarrow x = \frac{1}{\lambda}Ax, \tag{3.3}$$

where λ is the largest eigenvalue of A. Intuitively, a node has high eigenvector centrality if it is connected to many other nodes, but also weighing in how central these nodes are. Bonacich and Lloyd (2001) introduce the concept of *alpha centrality*, defined by

$$x = \alpha A x + E, \tag{3.4}$$

where E is a network-exogenous determinant of centrality and α is a weighting factor. A technical restriction on α is that it must be smaller than $1/\lambda$. As $\alpha \to 1/\lambda$, alpha centrality converges to the standard eigenvector centrality from equation (3.3); that is, for high α the exogenous factors E cease to matter. For some intuition on the alpha centrality measure, consider a social-networks application where x is a measure of prestige or popularity. Equation (3.4) says that prestige is higher if the node itself has high exogenous prestige, if the node is connected to many other nodes, and if the node's "average connection" also has high prestige (for network or exogenous reasons). In my setting, the exogenous variable E is whether or not a particular firm engages in M&A activity and the adjacency matrix A corresponds to inter-firm alliances.[6] Since I do not assume a firm's own M&A activity to cause, by itself, future M&A activity, I exclude the direct effect of own exogenous factors in alpha centrality by computing an adjusted measure $x_{adj.}$:

$$x_{adj.} = x - E \tag{3.5}$$

for firms with one or more links, and zero otherwise. I denote my new measure as $x_{adj.}$ *merger centrality* and it aims to quantify how exposed a particular firm is to the reallocation shocks arising from M&A activity occurring throughout the economy.[7] I use similar econometric specifications as for my main analysis and expect high merger centrality to predict future M&A activity. Results are reported in Table 3.7 for three alternative levels of the eigenvalue-normalized weighing factor α/λ: 0.1, 0.5, and 0.9.

Each model in Table 3.7 includes my new merger centrality variable, CEN, and an additional control, $DEGREE$, which counts the number of links. The inclusion of the latter allows me to differentiate my story about proximity to M&A

[6] For computational reasons, large networks become intractable, so I adopt the assumption that alliances last only for five years.

[7] Note that this potentially includes M&A activity triggered in the past by the firm's own mergers and then "feeds back" but does not include a direct effect from own M&A.

Table 3.7: Merger Propagation and Merger Centrality.

This table shows OLS regressions where the dependent variable is $MA_{i,t}$, a dummy taking the value of one if firm i is engaged in merger activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, PMA, which indicates whether the firms' partners were involved in a merger deal in the past year, CEN, the merger centrality variable following Bonacich and Lloyd (2001), and $DEGREE$, which counts the number of alliances. t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	$\alpha/\lambda = 0.1$		$\alpha/\lambda = 0.5$		$\alpha/\lambda = 0.9$	
	(1)	(2)	(3)	(4)	(5)	(6)
PMA	0.0467***	0.0108	0.0508***	0.0144	0.0605***	0.0215*
	(0.0105)	(0.0125)	(0.0102)	(0.0120)	(0.0100)	(0.0115)
CEN	2.312***	1.737**	0.276***	0.205**	0.0148*	0.0118
	(0.536)	(0.790)	(0.0656)	(0.103)	(0.00810)	(0.0108)
$DEGREE$	0.000454	-0.000364	0.000415	-0.000375	0.00206	0.000373
	(0.00105)	(0.000793)	(0.00109)	(0.000817)	(0.00133)	(0.000851)
$PART$	0.153***	0.0462***	0.152***	0.0457***	0.150***	0.0447***
	(0.00780)	(0.00982)	(0.00780)	(0.00982)	(0.00790)	(0.00984)
ROA	0.184***	0.109***	0.184***	0.109***	0.184***	0.109***
	(0.0106)	(0.0142)	(0.0106)	(0.0142)	(0.0106)	(0.0142)
$SIZE$	0.0156***	0.0132***	0.0156***	0.0132***	0.0157***	0.0134***
	(0.00153)	(0.00382)	(0.00153)	(0.00382)	(0.00153)	(0.00382)
$BLEV$	-0.0589***	-0.169***	-0.0586***	-0.169***	-0.0588***	-0.170***
	(0.00896)	(0.0120)	(0.00896)	(0.0120)	(0.00896)	(0.0120)
MTB	0.00141***	0.00201***	0.00141***	0.00201***	0.00141***	0.00201***
	(0.000216)	(0.000267)	(0.000216)	(0.000267)	(0.000216)	(0.000267)
$SGROWTH$	0.00236***	0.000235	0.00236***	0.000233	0.00238***	0.000235
	(0.000736)	(0.000879)	(0.000736)	(0.000879)	(0.000737)	(0.000878)
AGE	0.000946***	-0.139	0.000953***	-0.110	0.000958***	-0.0994
	(0.000201)	(1.808)	(0.000202)	(1.808)	(0.000202)	(1.917)
N	70922	70922	70922	70922	70922	70922
R^2	0.174	0.446	0.174	0.446	0.170	0.446
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

activity from factors that might simultaneously result in a firm having many partners and engaging in M&A with a high likelihood. My analysis focuses on one-year lags in terms of past merger activity. The merger centrality variable is, as expected, positive. The coefficient is statistically significant in most specifications, despite including localized M&A activity (i.e., involving own partners) as a regressor (PMA variable). The centrality effect becomes statistically weaker as α/λ increases, that is, as my measure converges to standard eigenvector centrality (see in particular specification (6)). This suggests that centrality by itself does not matter for merger propagation, but rather it is associated with proximity to firms that are indeed engaging in M&A. The economic magnitude of the centrality effect is also significant. Considering, for instance, model (4), a one-standard-deviation increase in centrality is associated with an additional 3.4% (0.205 x 0.168) likelihood of merging. This is an increase of about 17% relative to the unconditional M&A probability.

3.4.2 Does partner M&A cause future alliances?

My main hypothesis is that partner mergers create incentives for firms to engage in M&A activity. My rationale is that a reactive M&A event corresponds to a multilateral organizational response to deal with the resource-reallocation effects of partners engaging in mergers. This mechanism notwithstanding, it is only natural to ask whether partner mergers trigger other kinds of responses from firms. In this section, in particular, I test the hypothesis regarding whether partner mergers increase the likelihood that a firm engages in new alliances. This hypothesis is consistent with some alliances having important fixed setup costs. It would then follow that the gains associated with setting up a certain alliance potentially change with a partner merger, and the same logic I offer for merger propagation would apply. The empirical results are contained in Table 3.8, which uses the same specifications as Table 3.3, except for replacing the dependent variable with a dummy indicating whether or not the firm enters a new alliance.

Models (1)-(5) show that the effect is statistically significant, even after controlling for firm characteristics and the various fixed effects. The economic magnitude of the effect, in relative terms, is much higher than the merger propagation effect. Even for the most stringent regression, where a partner merger generates an additional alliance probability of about 1.8%, this is almost a 40% increase relative to the unconditional likelihood that a public firm will enter into an alliance (about 5%).

Table 3.8: Partner Alliance Activity and the Likelihood of Forming Alliances.

This table shows OLS regressions where the dependent variable is $AL_{i,t}$, a dummy taking the value of one if firm i is engaged in alliance activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, and $PART \times PMA$, which indicates whether the firms' partners were involved in a merger deal in the past. The subscript on PMA indicates the lag in years. t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

	(1)	(2)	(3)	(4)	(5)
PMA_1	0.146***	0.136***	0.126***	0.0229***	0.0182**
	(0.00863)	(0.00826)	(0.00818)	(0.00785)	(0.00865)
PMA_2	0.0849***	0.0770***	0.0734***	-0.00504	-0.00360
	(0.00825)	(0.00792)	(0.00796)	(0.00777)	(0.00858)
$PART$	0.128***	0.127***	0.126***	0.183***	0.186***
	(0.00469)	(0.00469)	(0.00479)	(0.00677)	(0.00772)
ROA		-0.0230***	-0.00803	-0.0102	-0.00660
		(0.00560)	(0.00664)	(0.00710)	(0.00859)
$SIZE$		0.0108***	0.0129***	0.00810***	0.00694***
		(0.000658)	(0.000818)	(0.00166)	(0.00198)
$BLEV$		-0.0369***	-0.0191***	-0.00708	-0.00359
		(0.00425)	(0.00448)	(0.00514)	(0.00616)
MTB		0.000765***	0.000524***	0.000167	0.000109
		(0.000124)	(0.000125)	(0.000114)	(0.000131)
$SGROWTH$		0.00108***	0.000935**	0.000247	0.000162
		(0.000354)	(0.000380)	(0.000357)	(0.000419)
AGE		-0.0000603	0.000231*	-0.00407***	-0.106
		(0.000127)	(0.000137)	(0.000834)	(0.806)
N	75994	75994	75994	75994	75994
R^2	0.250	0.260	0.319	0.472	0.517
Year FE	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	No	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes

These results are interesting on their own, but they are also relevant to my main story about merger propagation because establishing new alliances creates additional opportunities for merger propagation. This suggests that the economic magnitudes I report in the main analysis are conservative relative to the total effect that alliance links may have as channels for merger diffusion.

3.4.3 Endogeneity

Although I have employed highly restrictive tests with such controls as SIC3-year and firm fixed effects to exclude the possibility that my results are driven by aggregate shocks or firm unobservables, a specific endogeneity concern may still exist and have been overlooked. That is, an alliance becomes unsuccessful and, therefore, each of its members in turn looks for a new partner and engages in an M&A. In this case, one partner's merger is not caused by the other's, but both mergers are the result of a bad alliance and nonetheless misinterpreted as strategic complements.

This is the omitted variable problem in that alliance performance is left out of my specifications and may not be taken care of by my exhaustive list of fixed effects because this variable can be time-varying in nature. I conduct several additional tests to resolve this concern. First, as no direct information regarding alliance performance is available, I rely on partners' performance to proxy for their alliance performance. Two firms form a corporate alliance to share resources and gain a synergy that each could not have on its own and, therefore, in concept the realized synergy measures the alliance performance and is reflected in each member's ex-post performance. Following this idea, I use the information on each alliance member's change in operating or stock performance to represent the realized synergy of the alliance and thus the alliance performance. Specifically, I compute each alliance member's change in its operating or stock performance since the start of the alliance and average this measure across members (see below). $ROA_{i,t}$ is the alliance member i's profitability in year t measured by operating income before depreciation normalized by total assets while $ROA_{i,0}$ is the firm's profitability the year before the alliance is created. Likewise, I also use firm stock performance $RETURN$ to measure the counterpart of the alliance, where $RETURN_{i,t}$ is firm i's average monthly return in year t.

$$ALLIANCE\ ROA_t = \sum_{i=1}^{n} \frac{ROA_{i,t} - ROA_{i,0}}{n}$$

$$ALLIANCE\ RETURN_t = \sum_{i=1}^{n} \frac{RETURN_{i,t} - RETURN_{i,0}}{n}$$

I redo my main test with alliance performance controlled for and present the results in Table 3.9, where Column 1 shows the benchmark case without either of the two variables, Column 2 includes $ALLIANCE\ ROA$, Column 3 adds $ALLIANCE\ RETURN$, and the last column has both. As one can see, the results regarding my coefficients of interest change little across specifications and, therefore, my propagation story is not rejected. In fact, $ALLIANCE\ ROA$'s coefficients are significant while $ALLIANCE\ RETURN$'s are not.

To be more conservative, I exclude "bad" alliances and rerun the test (see Table 3.10). With Column 1 of Table 3.10 being the benchmark, Column 2 drops observations whose $ALLIANCE\ ROA$ is below the median, Column 3 drops cases in which $ALLIANCE\ RETURN$ is below the median, and Column 4 requires both the firm's $ALLIANCE\ ROA$ and its $ALLIANCE\ RETURN$ to be above the median. The results show that the coefficients from the sub-sample tests are as statistically and economically significant and therefore my results from the main table are not driven by alliance members quitting the alliance sequentially following its bad performance.

Next, I perform the IV tests where I instrument the potential endogenous variable, firm partner merger event (i.e.,PMA), with the industry-level merger waves. These merger shocks occur at the industry level and thus should not be correlated with an individual firm's or its alliance's specifics. The advantage of this approach is its generality in that it can solve the omitted variable problem not only with regard to alliance performance but also with any potential firm-level unobservable. On the other hand, my test can still accommodate the inclusion of the firm's own industry-year fixed effects as its partner is not necessarily from the same industry. For the instrument, I choose SIC2-year fixed effects rather than SIC3 or SIC4 because I do not want the industry classification to be so fine that the proxied macro-level shocks are correlated with firm-level shocks. Table 3.11 presents the results: Columns 1 and 2 show the benchmark coefficients without the IVs, one with the industry-year fixed

Table 3.9: Controlling for Alliance Performance.

This table shows OLS regressions where the dependent variable is $MA_{i,t}$, a dummy taking the value of one if firm i is engaged in merger activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, and PMA, which indicates whether the firms' partners were involved in a merger deal in the past. The subscript on PMA indicates the lag in years. $ALLIANCE\ ROA$ is measured by within the firm's alliance taking the average of the change in firm profitability since the start of the alliance. $ALLIANCE\ RETURN$ is measured by within the firm's alliance taking the average of the change in firm stock return since the start of the alliance. t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)
PMA_1	0.0598***	0.0599***	0.0601***	0.0600***
	(0.0109)	(0.0109)	(0.0109)	(0.0109)
PMA_2	0.0325***	0.0326***	0.0330***	0.0329***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)
$ALLIANCE\ ROA$		0.145***		0.138***
		(0.0496)		(0.0508)
$ALLIANCE\ RETURN$			0.113	0.0645
			(0.0922)	(0.0944)
$PART$	0.153***	0.153***	0.153***	0.153***
	(0.00956)	(0.00959)	(0.00958)	(0.00960)
ROA	0.173***	0.167***	0.172***	0.167***
	(0.0109)	(0.0111)	(0.0109)	(0.0111)
$SIZE$	0.0152***	0.0154***	0.0152***	0.0154***
	(0.00155)	(0.00155)	(0.00155)	(0.00155)
$BLEV$	-0.0553***	-0.0549***	-0.0552***	-0.0548***
	(0.00923)	(0.00924)	(0.00924)	(0.00924)
MTB	0.00125***	0.00122***	0.00124***	0.00121***
	(0.000223)	(0.000223)	(0.000223)	(0.000224)
$SGROWTH$	0.00243***	0.00235***	0.00242***	0.00235***
	(0.000763)	(0.000762)	(0.000762)	(0.000761)
AGE	0.000680***	0.000680***	0.000677***	0.000678***
	(0.000213)	(0.000213)	(0.000213)	(0.000213)
N	70475	70475	70475	70475
R^2	0.167	0.167	0.167	0.167
Industry x Year FE	Yes	Yes	Yes	Yes

Table 3.10: Using "Good" Alliances.

This table shows OLS regressions where the dependent variable is $MA_{i,t}$, a dummy taking the value of one if firm i is engaged in merger activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, and PMA, which indicates whether the firms' partners were involved in a merger deal in the past. The subscript on PMA indicates the lag in years. Column 1 includes all alliances. Column 2 includes alliances with above-median $ALLIANCE\ ROA$ while column 3 has alliances with above-median $ALLIANCE\ RETURN$. Column 4 includes alliances whose $ALLIANCE\ ROA$ and $ALLIANCE\ RETURN$ both are above their medians respectively. t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)
PMA_1	0.0598***	0.0619***	0.0791***	0.0688***
	(0.0109)	(0.0156)	(0.0156)	(0.0208)
PMA_2	0.0325***	0.0465***	0.0336**	0.0575***
	(0.0110)	(0.0151)	(0.0152)	(0.0199)
$PART$	0.153***	0.173***	0.155***	0.169***
	(0.00956)	(0.0128)	(0.0124)	(0.0157)
ROA	0.173***	0.152***	0.162***	0.153***
	(0.0109)	(0.0110)	(0.0111)	(0.0110)
$SIZE$	0.0152***	0.0129***	0.0120***	0.0109***
	(0.00155)	(0.00156)	(0.00155)	(0.00155)
$BLEV$	-0.0553***	-0.0473***	-0.0458***	-0.0406***
	(0.00923)	(0.00940)	(0.00935)	(0.00946)
MTB	0.00125***	0.000957***	0.000967***	0.000837***
	(0.000223)	(0.000226)	(0.000225)	(0.000225)
$SGROWTH$	0.00243***	0.00195**	0.00235***	0.00206***
	(0.000763)	(0.000771)	(0.000772)	(0.000777)
AGE	0.000680***	0.000554**	0.000631***	0.000559**
	(0.000213)	(0.000225)	(0.000224)	(0.000231)
N	70475	64475	64475	61938
R^2	0.167	0.166	0.161	0.159
Industry x Year FE	Yes	Yes	Yes	Yes

effects and one without, and Columns 3 and 4 present the results with the IVs. The coefficient of interest (i.e., PMA) is in fact a bit larger in the IV tests. As surprising as it may seem, it is not unreasonable to observe the coefficient become bigger on second thought. It is not totally clear in what direction the endogeneity influences my results. For example, it is possible that the merger becomes unsuccessful because one member is simply not suitable for the alliance or no longer needs a complementary partner and thus breaks the alliance. In this case, the firm's partner will look for a new collaborator to replace the firm's role while the firm itself will stop looking for a partner. If my sample captures some of those cases, then the non-IV tests will underestimate the propagation effect, which will become larger with IVs.

Table 3.12 reflects the redo of the tests presented in Table 3.11 using the subsample where a firm and its alliance partner come from different industries (i.e., with different SIC2s). As shown, the results are highly similar to those from Table 3.11, suggesting once again that my interpretation of firm merger predictability from its alliance partner merger as economic-link led merger propagation is robust and free from the endogeneity problem that results from an omitted firm-level variable.

3.4.4 Robustness checks

This section summarizes the robustness checks I conduct for the main test. I do not present the associated tables for brevity. The rationale and outcome of these tests are as follows:

1. **Alliance duration.** Since almost no information on alliance termination and/or expected duration is available, in my main analysis I assume that alliances last forever (i.e., a maximum of 21 years given the length of my dataset). I adopt the alternative assumptions that alliances last 5 years or 10 years and find similar results.

2. **Logit specification.** I use linear probability models in my main analyses because these models are computationally tractable and allow for the inclusion of a rich set of fixed effects. For specifications where it is computationally feasible, I run my main test using a logit model, with similar qualitative results.

3. **Sample restricted to firms with alliances.** My sample includes firms with and without alliances and most of the firm-years (about 80%) correspond to

Table 3.11: IV Test.

This table shows regressions where the dependent variable is $MA_{i,t}$, a dummy taking the value of one if firm i is engaged in merger activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, and PMA, which indicates whether the firms' partners were involved in a merger deal in the past. The first two columns refers to OLS regressions while the last two are 2SLS regressions where PMA is instrumented by industry merger waves (i.e., SIC2 $\times$ year fixed effects). t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)
PMA	0.0810***	0.0821***	0.116***	0.118***
	(0.00941)	(0.00936)	(0.0171)	(0.0108)
$PART$	0.144***	0.142***	0.128***	0.125***
	(0.00738)	(0.00747)	(0.00984)	(0.00628)
ROA	0.212***	0.176***	0.215***	0.178***
	(0.00980)	(0.0106)	(0.00981)	(0.00915)
$SIZE$	0.0117***	0.0180***	0.0111***	0.0173***
	(0.00135)	(0.00153)	(0.00136)	(0.000877)
$BLEV$	-0.0525***	-0.0604***	-0.0503***	-0.0595***
	(0.00866)	(0.00899)	(0.00867)	(0.00666)
MTB	0.00126***	0.00137***	0.00122***	0.00134***
	(0.000212)	(0.000218)	(0.000212)	(0.000198)
$SGROWTH$	0.00312***	0.00246***	0.00312***	0.00247***
	(0.000704)	(0.000745)	(0.000705)	(0.000771)
AGE	0.000623***	0.000796***	0.000600***	0.000756***
	(0.000199)	(0.000206)	(0.000198)	(0.000112)
N	75965	75965	75965	75965
R^2	0.069	0.168	0.069	0.166
Year FE	Yes	Yes	Yes	Yes
Industry x Year FE	No	Yes	No	Yes

Table 3.12: IV Tests-Alliances Across Industries.

This table shows regressions using the sample of alliances where the partners are from different industries based upon SIC2. The dependent variable is $MA_{i,t}$, a dummy taking the value of one if firm i is engaged in merger activity at time t and zero otherwise. The main dependent variables are $PART$, which is a dummy variable indicating if the firm is engaged in alliance activity at time t, and PMA, which indicates whether the firms' partners were involved in a merger deal in the past. The first two columns refers to OLS regressions while the last two are 2SLS regressions where PMA is instrumented by industry merger waves (i.e., SIC2 $\times$ year fixed effects). t-statistics are presented in parentheses; statistical significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)
PMA	0.0817***	0.0877***	0.107***	0.116***
	(0.0107)	(0.0107)	(0.0188)	(0.0116)
$PART$	0.145***	0.140***	0.134***	0.128***
	(0.00791)	(0.00799)	(0.0102)	(0.00636)
ROA	0.208***	0.173***	0.210***	0.174***
	(0.00991)	(0.0108)	(0.00992)	(0.00938)
$SIZE$	0.00979***	0.0159***	0.00942***	0.0154***
	(0.00134)	(0.00154)	(0.00136)	(0.000883)
$BLEV$	-0.0480***	-0.0569***	-0.0468***	-0.0562***
	(0.00876)	(0.00912)	(0.00877)	(0.00673)
MTB	0.00114***	0.00124***	0.00111***	0.00122***
	(0.000213)	(0.000221)	(0.000213)	(0.000202)
$SGROWTH$	0.00315***	0.00240***	0.00315***	0.00240***
	(0.000711)	(0.000757)	(0.000712)	(0.000786)
AGE	0.000735***	0.000875***	0.000712***	0.000840***
	(0.000204)	(0.000213)	(0.000203)	(0.000114)
N	72505	72505	72505	72505
R^2	0.062	0.165	0.056	0.163
Year FE	Yes	Yes	Yes	Yes
Industry x Year FE	No	Yes	No	Yes

firms without alliances. This large set of firms gives me statistical power to identify highly-dimensional time-varying industry fixed effects. Furthermore, for regressions with firm fixed effects, I obtain additional statistical power from including observations for the same firm for periods in which the firm did not have alliances. Naturally, I control for differences across firms that have alliances (or not) by including a control variable (dummy $PART$), but one may worry that the coefficients on firm characteristics differ across these subsamples. Therefore, I redo my main test restricting it to a sample where all firms have alliances. The results are qualitatively similar for the regressions without firm fixed effects (although weaker).

4. **Continuous explanatory variables.** My main explanatory variable is a dummy indicating whether or not a firm's partners engaged in M&A activity. It is also natural to define this variable in a more continuous way. Following this logic, in running my tests, I replace the dummy $PART$ (indicating whether a firm has alliances or not) with a variable that counts a firm's number of partners and I replace the dummy PMA (indicating whether or not a partner merger took place) with a variable measuring the percentage of partners engaged in M&A. The results are qualitatively similar and statistically significant across specifications.

5. **Excluding mergers by alliance partners.** In the way I define my explanatory variables, some mergers may actually involve two partners in an alliance. This occurs infrequently, but to ensure that it is not driving my results, I run my main test dropping these observations.

6. **Joint venture (JV) connections.** I consider any strategic alliance in my main analysis. This includes truly collaborative projects such as JVs, but perhaps also other links that are more indicative of a customer-supplier relationship. To differentiate my story from alternatives based on customer-supplier connections, I run my main regression with only JVs counting as inter-firm alliance links. Naturally I lose much statistical power because JVs are only a fraction of total alliances. Nevertheless, for specifications without firm fixed effects, my main results are statistically significant with similar magnitudes. For specifications with firm fixed effects, the coefficients on partner mergers are positive but not statistically significant.

7. **Within-alliance asymmetry.** In my final robustness check I consider asymmetries between within-alliance firms. My concern is that my story seems less plausible for alliances where one partner is much larger than the other. Consider first the case in which a small firm is a partner of a big firm, and the big firm engages in M&A. It seems less likely that M&A activity by this big firm would be related to another firm acquiring it to divert resources. On the other hand, if a big firm has a small partner that is acquired by a third firm and resources are diverted away from the alliance, this may have little impact for the big firm just because of the size differential. Motivated by this rationale, I run a regression where an alliance link is only defined to exist for pairs of firms in the bottom quartile of absolute size dispersion. Although I lose statistical power, the results are still qualitatively similar and statistically significant for all but the most stringent regression. Moreover, the economic magnitude of the results is actually higher than in my baseline specification where all alliances are included.

3.5 Conclusion

My paper proposes a novel channel for merger propagation across the economy. Firms that pool resources to undertake joint projects are exposed to resource allocation externalities associated with their partners' M&A activity. I show with data that partner mergers are indeed associated with higher future M&A likelihood. These effects are not explained by time-varying industry M&A activity or firm characteristics (observable or unobservable) and are economically meaningful. Although I treat whether such externalities exist as a first-stage question, the positive answer leads to a follow-on question of what type of externalities (positive or negative) dominates merger propagation within an alliance, which I deem equally important and interesting and thus leave for future research.

Appendix

Proof of implication 2.2.1. At $t = 2$, assume that such a pure strategy equilibrium exists. Banks of the same type have no incentive to share deals with each other because of no synergy gain. For a normal-monitoring pair, if a normal bank is matched with a medium firm and its connected bank happens not to be with a medium firm, a synergy from restoring the matching efficiency can be gained by the relationship bank referring its firm to the connected bank, in which situation the three parties can coordinate such that everyone is better off. The medium firm definitely has an incentive to be referred; otherwise, it would be left to the market and get no funding at all, as $\frac{q_m+q_b}{2}x - 1 - c < 0$. Both the relationship bank and the connected bank have an incentive too as they can share some of the enlarged "pie". In the model, for simplicity, they are assumed to have zero bargaining power and so in equilibrium transferring the firm weakly dominates the alternative. Likewise, if the monitoring bank in a normal-monitoring pair is matched with a good firm while its connected bank is not, all associated parties have an incentive to restore the local matching efficiency by the relationship bank's transferring the firm to its connected partner. Normal banks can break even only with good firms while monitoring banks can break even with medium firms although this would not be a first-best outcome (i.e., $q_g x - 1 > q_g x - 1 - c > 0$ as $q_m x - 1 - c > 0$). This can occur when the monitoring bank is not connected to a normal monitoring bank or its connected bank's capital constraint is binding, in which case the firm is still better off than being left to the market for funding. See Table 13 for detailed financing flows.

■

Proof of implication 2.2.2. Use Δq to denote the change in a firm's quality. Firm type at $t = 1$ is observable and, therefore, Δq in fact represents the shock. The degree of the shock can be quantified by the magnitude of Δq, namely $|\Delta q|$, which has four possible values, $q_g - q_m$, $q_g - q_b$, $q_m - q_b$, and 0; $q_g - q_b$ or $q_m - q_b$ occurs when a qualified firm becomes an unqualified (i.e., bad), and therefore does not get funding anywhere. Those observations will not show up in the data by the theory, and therefore I only have to compare a firm with a shock magnitude $q_g - q_m$ and one with no shock. The probability of a firm going to a connected bank conditional on

Table 13: Static: Financing Flow.

The table presents a tree of probabilities conditional on a firm's bank or firm type, its connected bank's type, its shock type, its connected bank's shock type, and the corresponding equilibrium outcomes: whether the relationship bank continues with the firm, whether it transfers the firm, and whether there is a first-best matching.

Bank/Firm Type	C's Type	Firm Type	C's Firm Type	Continue?	Share?	First Best?
			G (1/3)	Y	N	N
		G (1/3)	M (1/3)	Y	N	N
			B (1/3)	Y	N	N
			G (1/3)	Y	N	Y
	Mo (m)	M (1/3)	M (1/3)	Y	N	Y
			B (1/3)	Y	N	Y
			G (1/3)	N	N	Y
		B (1/3)	M (1/3)	N	N	Y
			B (1/3)	N	N	Y
Mo/M (m)						
			G (1/3)	Y	N	N
		G (1/3)	M (1/3)	N	Y	Y
			B (1/3)	N	Y	Y
			G (1/3)	Y	N	Y
	No ($1-m$)	M (1/3)	M (1/3)	Y	N	Y
			B (1/3)	Y	N	Y
			G (1/3)	N	N	Y
		B (1/3)	M (1/3)	N	N	Y
			B (1/3)	N	N	Y
			G (1/3)	Y	N	Y
		G (1/3)	M (1/3)	Y	N	Y
			B (1/3)	Y	N	Y
			G (1/3)	N	Y	Y
	Mo (m)	M (1/3)	M (1/3)	N	N	N
			B (1/3)	N	Y	Y
			G (1/3)	N	N	Y
		B (1/3)	M (1/3)	N	N	Y
			B (1/3)	N	N	Y
No/G ($1-m$)						
			G (1/3)	Y	N	Y
		G (1/3)	M (1/3)	Y	N	Y
			B (1/3)	Y	N	Y
			G (1/3)	N	N	N
	No ($1-m$)	M (1/3)	M (1/3)	N	N	N
			B (1/3)	N	N	N
			G (1/3)	N	N	Y
		B (1/3)	M (1/3)	N	N	Y
			B (1/3)	N	N	Y

a shock with a magnitude of $q_g - q_m$ is,

$$Prob(B = C \mid |\Delta q| = q_g - q_m) = \frac{m(1-m)/3 \times 2/3 + (1-m)m/3 \times 2/3}{m^2/3 + m(1-m)/3 + (1-m)m/3 \times 2/3} > 0.$$

When a firm receives no shock, it simply stays with its relationship bank, that is, $Prob(B = C \mid |\Delta q| = 0) = 0$. It is easy to see that $Prob(B = C \mid |\Delta q| = q_g - q_m) > Prob(B = C \mid |\Delta q| = 0)$. ■

Proof of implication 2.2.3 There are two cases of a shock with the magnitude of $|\Delta q| = q_g - q_m$. When a good firm of $t = 1$, which is matched with a normal bank, receives a negative shock, $\Delta q = q_m - q_g < 0$, and becomes medium, the connected bank to which it switches will be a monitoring bank. Mathematically, the probability of a connected bank being a monitoring type, $B = C$, conditional on a negative shock can be written as,

$$Prob(B = Mo \mid B = C \& \Delta q = q_m - q_g) = \frac{(1-m)m/3 \times 2/3}{(1-m)m/3 \times 2/3} = 1.$$

Likewise, a positive shock associated with a firm's switching to a connected bank occurs when a medium firm is matched with a monitoring bank and is migrated to a normal bank for a good shock, $\Delta q = q_g - q_m < 0$. Hence, its conditional probability of migrating to a monitoring bank is,

$$Prob(B = Mo \mid B = C \& \Delta q = q_g - q_m) = \frac{0}{m(1-m)/3 \times 2/3} = 0.$$

■

Proof of implication 2.2.4 The conditional probability of a firm going to a connected bank on a negative shock can be represented as follows,

$$Prob(B = C \mid \Delta q = q_m - q_g) = \frac{(1-m)m/3 \times 2/3}{(1-m)m/3 \times 2/3} = 1.$$

The conditional probability of a firm going to a connected bank on a positive shock can be shown as,

$$Prob(B = C \mid \Delta q = q_g - q_m) = \frac{m(1-m)/3 \times 2/3}{m/3} = 2/3(1-m) < Prob(B = C \mid \Delta q = q_m - q_g).$$

■

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