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Essays on Bank Loans, Deposit Insurance, and Deregulation

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ESSAYS ON BANK LOANS, DEPOSIT INSURANCE, AND DEREGULATION

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DEDICATION

To my parents, Chaeruddin and Khusnul Fatimah, who have patiently and lovingly taken care of me and endorsed me to pursue higher education.

To my lovely wife, Sari Murtiasih, who always trusts in me and have been my constant source of loves, supports, encouragement, and prayers.

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ABSTRACT

In my first essay, using a novel dataset that merges the Dealscan database and 8-Ks between 1994-2014, I find that on average, only about 31% of bank loans are announced by firms. Among those loans announced, about 60% are cleanly announced and 40% are announced together with other events. The three-day Cumulative Abnormal Stock Return (CAR) following a loan announcement is positive and both statistically and economically significant, which on average about +39 b.p., in line with the theory of bank loan specialness. This finding is mainly driven by bank-dependent firms. Next, I find significant evidence of sample selection bias in the loan announcements sample, which likely confounds the findings from the previous literature. Correcting for the bias, I find that a loan is more likely to be announced during a market crisis, relative to normal times, but not during a banking crisis. Moreover, a loan is more likely to be announced by small firms, firms with lower EBITDA, and when the loan has more financial covenants, is a revolver loan, has a longer maturity, secured, and when the firm has a previous lending relationship. Then, CARs are significantly higher during a banking crisis, compared to normal times, but not in a market crisis, in line with both the asymmetric information hypothesis and the institutional memory hypothesis. Lastly, I find strong evidence that CARs are negatively associated with the market share of nonbank lenders, which aligns with the competition hypothesis between bank and nonbank lenders.

In my second essay, using a natural experiment of changes in deposit insurance deposit insurance coverage limit over 2002-2011 in Indonesia, I find a significant positive relation between explicit deposit insurance coverage and bank risk-taking, consistent with the moral hazard hypothesis. More specifically, controlling for various bank-specific and macroeconomic variables, as well as bank regulations, I find that Indonesian banks' *Z-Score*, an inverse measure of bank risk taking, increases on average about 18% when the government switched from the blanket guarantee era to the limited guarantee era. Further, I find some evidence that the relation is non-monotonic at the low level of explicit deposit insurance coverage, in line with the safety net hypothesis. Finally, I find significant evidence that the impact of explicit deposit insurance coverage on bank risk is different across different kinds of ultimate owners. In particular, family banks and politically connected banks are those that are most affected when the government switched from the blanket guarantee era to the limited guarantee era, suggesting that the moral hazard problem in these banks are more prominent compared to foreign banks and nonpolitically connected banks.

In my third essay (co-authored with Allen N. Berger, Sadok El Ghoul, and Omrane Guedhami), we examine the impact of geographic deregulation on bank risk. More specifically, we study all three types of geographic deregulation in last three decades in the U.S. banking industry—intrastate branching, interstate banking, and interstate branching. These deregulations provide unique empirical settings to test the impact of competition and diversification on bank risk. We find statistically and economically significant evidence that on average, interstate banking deregulation is associated with about 22% increase in *Z-score*, an inverse indicator of overall bank risk.

On the contrary, we find some evidence that intrastate branching is associated with a decrease in *Z-score* about 3%. Meanwhile, we find no evidence that interstate branching affects bank risk. These findings are robust to a variety of sensitivity checks, including those for endogeneity and sample selection bias, as well as alternative risk measures. Different than most of the previous studies that focus on large banks and Bank Holding Companies, our findings show that the favorable impact of interstate banking deregulation on bank risk are driven by small banks, which had opposed the deregulation with the fear that an increase in competition from large banks could reduce their survival probability. Meanwhile, intrastate branching is associated with higher risk for small and medium banks, but lower risk for large banks. These findings suggest that the competition-stability channel dominates for small and medium banks, while the diversification-stability channel dominates for large banks.

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CHAPTER 1

INTRODUCTION

Banks are firms that collect deposits from the public and use the pool of funds collected to provide funding to borrowing firms. Prior to a lending decision, a bank screens each loan applications to gather private information about the borrowing firms, which are mainly from the previous banking relationship between the bank and the borrowing firms. Post a lending decision, the bank conduct continuous monitoring to the borrowing firms and gather more private information about their ability to repay the bank loans. This specialization in screening and monitoring the borrowing firms gives banks a comparative advantage in reducing asymmetric information problem between the borrowing firms and investors, compared to other arms' length lenders (Leland and Pyle, 1977), and thus, makes banks "special" institutions.

The first essay in this dissertation, **"Are Bank Loans Special? Evidence from Normal Times and Financial Crises"**, provides empirical evidence of the certification value of bank loans from the U.S. market in the last two decades, which has experienced both market crisis and banking crisis. Using a novel dataset that merges 11,635 loan deals from the LPC Dealscan database and form 8-Ks from the SEC EDGAR between 1994-2014, I find that on average, only about 31% of bank loans are announced by firms. Among those loans announced, about 60% are cleanly announced and 40% are announced together with other events.

Next, I find statistically and economically significant three-days Cumulative Abnormal Stock Return (CAR) following a loan announcement, which on average about +39 b.p., in line with the theory of bank loan specialness. The positive CARs are driven mainly by bank-dependent firms, which have never issued public bonds. Meanwhile, as a comparison, I show that three-days CARs following public bond announcements by firms in the sample are negative and statistically significant. Then, using the enactment of Sarbanes-Oxley Act of 2002 (SOX) and the SEC Rule ##33-8400 of 2004 as exogenous shocks to loan announcements by firms, I show significant evidence of sample selection bias in the loan announcements sample, which likely confounds the findings from the previous literature.

Being the first study that corrects the sample selection bias, using the Heckman selection method, I find that a loan is more likely to be announced during a market crisis, relative to normal times, but not during a banking crisis, consistent with the asymmetric information hypothesis. Moreover, a loan is more likely to be announced by small firms, firms with lower EBITDA, and when the loan has more financial covenants, is a revolver loan, has a longer maturity, secured, as well as when the firm has a previous relationship with the same lender in the past 5 years. Then, I find that the CARs are significantly higher during a banking crisis, compared to normal times, but not in a market crisis, in line with both the asymmetric information hypothesis and the institutional memory hypothesis.

In terms of loan, firm, and lender characteristics, CAR is statistically higher for a loan announced by a bank-dependent firm, and for a loan that has more financial covenants, and is a revolver. I also find some evidence CAR is statistically higher for a loan that has a longer maturity as well as a loan made by the same lender that has lent the firm in the past 5 years. Finally, I find strong evidence that CAR is negatively associated with the market share of nonbank lenders, which aligns with the competition hypothesis that explains why CARs following loan announcements shown by the recent literature, including this paper, is not as high as the earlier studies have shown.

My first essay provides us an explanation of the specialness of banks in private information gathering that can reduce information asymmetries between borrowing firms and investors. However, due to the nature of their business models, in which banks borrow short-term funding from depositors and then invest it on long-term assets in a form of bank lending, banks are prone to "bank runs" (Diamond and Dybvig, 1983). Due to their importance to the economy and the fragility nature, government provides protection to depositors in a form of deposit insurance, aside from implicit government guarantee in a form of bailouts. This deposit insurance system is increasingly popular in the last two decades. However, theory contends that deposit insurance can be a "double edged" sword. In particular, deposit insurance works like a put option to bank shareholders, which protects them from downside risks and therefore, provides them an incentive for a moral hazard problem. The second essay in this dissertation, **"Deposit Insurance Coverage, Ownership, and Risk Taking: Evidence from a Natural Experiment"**, aims to answer how deposit insurance affects bank risk-taking and how this relation works on banks with different types of ownership, by using a unique natural experiment data from Indonesia from 2002:Q1-2011:Q4.

I find a significant positive relation between explicit Deposit Insurance (DI) coverage and bank risk-taking, consistent with the moral hazard hypothesis. More specifically, controlling for various bank-specific and macroeconomic variables, as well as bank regulations, I find that Indonesian banks' *Z-score*, an inverse measure of bank risk taking, increases on average about 18% when the government switched from the blanket guarantee era to the limited guarantee era administered by the Indonesian Deposit Insurance Corporation (IDIC). In terms of mechanisms in which explicit DI coverage influences bank risk taking, I find that a lower explicit DI coverage is associated with lower bank profitability, lower standard deviation of profitability, and higher capitalization. Furthermore, I find some evidence that the relation is non-monotonic at the low level of explicit DI coverage, in line with the safety net hypothesis. This finding suggests that there is an optimum range of explicit DI coverage that sufficiently protects the depositors while curbing the banks' moral hazard problem. Finally, I find significant evidence that the impact of explicit DI coverage on bank risk is different across different kinds of ultimate owners. In particular, family banks and politically connected banks are those that are most affected when the government switched from the blanket guarantee era to the limited guarantee era, suggesting that the moral hazard problem in these banks are more prominent compared to foreign banks and nonpolitically connected banks.

The second essay shows that the moral hazard problem persists in the banking industry. This is one of the main reasons why the banking industry is highly regulated. However, a too strict bank regulation might hinder competition, which can lead to inefficient banking operations. Accordingly, when the regulation is deemed to be too strict, the government may conduct deregulation in the banking industry. Nevertheless, politicians and scholars are still debating whether deregulation can instead increase bank risk. My third essay in this dissertation (co-authored with Allen N. Berger, Sadok El

Ghoul, and Omrane Guedhami), **"Competition Does Not Kill Banks; It Makes Them Stronger: The Impact of Geographic Deregulation on Bank Risk,"** provides answers to this debate by examining the staggered geographic deregulation in the US banking industry. More specifically, we study all three types of geographic deregulation in last three decades in the U.S. banking industry—intrastate branching, interstate banking, and interstate branching. These deregulations provide unique empirical settings to test the impact of competition and diversification on bank risk.

We find statistically and economically significant evidence that on average, interstate banking deregulation is associated with about 22% increase in *Z-score*, an inverse indicator of overall bank risk. On the contrary, we find some evidence that intrastate branching is associated with a decrease in *Z-score* about 3%. Meanwhile, we find no evidence that interstate branching affects bank risk. These findings are robust to a variety of sensitivity checks, including those for endogeneity and sample selection bias, as well as alternative risk measures. Different than most of the previous studies that focus on large banks and Bank Holding Companies, our findings show that the favorable impact of interstate banking deregulation on bank risk are driven by small banks, which had opposed the deregulation with the fear that an increase in competition from large banks could reduce their survival probability. Meanwhile, intrastate branching is associated with higher risk for small and medium banks, but lower risk for large banks. These findings suggest that the competition-stability channel dominates for small and medium banks, while the diversification-stability channel dominates for large banks.

CHAPTER 2

ARE BANK LOANS STILL SPECIAL? EVIDENCE DURING NORMAL TIMES AND FINANCIAL CRISES[1,2]

2.1 INTRODUCTION

Are bank loans special compared to other sources of financing? Early theoretical works such as Diamond (1984, 1991), Ramakrishnan and Thakor (1984), Fama (1985), and Berlin and Loeys (1988) in general contend that banks can attenuate lenders-borrowers information asymmetry problem by gathering private information from their borrowing firms (screening) and actively conduct monitoring. In contrast, arm's-length investors (e.g. bondholders) can only rely on publicly available information and have limited monitoring ability. The bank specialization on screening and monitoring gives bank loans comparative advantages in form of lower contracting and monitoring costs, relative to public debts. Furthermore, borrowing firms will benefit from the reputation built by the monitoring activities of their banks. More specifically, good track records during active monitoring period by banks may serve as a positive signal which mitigates the renowned overvaluation problem of borrowing firms seeking external financing as

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noted by the traditional pecking order theory ála Myers-Majluf (Myers and Majluf, 1984).

Beside a solid theoretical body of literature on the “specialness” of bank loans compared to public debts, empirical studies on this view seem to provide mixed results. On the one hand, there is a large strand of literature confirming the theory, which finds significant certification value of bank loans in terms of positive abnormal stock returns following bank loan announcements (e.g. Mikkelson and Partch (1986), James (1987), Lummer and McConnell (1989), Slovin, Johnson, and Glascock (1992), Best and Zhang (1993), Hadlock and James (2002), Ross (2010), and Gande and Saunders (2012)). On the other hand, there is other strand of literature that contests this view by showing some empirical evidence that bank loans might not be special, or might be special but may depend on borrower and loan characteristics (e.g. Armitage (1995), Billet, Flannery, and Garfinkel (2006), Fields, Fraser, Berry, and Byers (2006), Bailey, Huang, and Yang (2011), Godlewski, Fungacova, and Weill (2011), Maskara and Mullineaux (2011), and Huang, Schwienbauer, and Zhao (2012)).

Despite the contentious debate, there are a number of compelling questions. First, bank loan announcements are voluntary and non-random events (Fery, Gasbarro, Woodliff, and Zumwalt, 2003; Maskara and Mullineaux, 2011), and therefore are potentially suffer from a self-selection bias. Surprisingly, there is no paper yet that I am aware of has corrected this bias. Next, if bank loans are special, does the specialness exist all the time or only during a particular time, or are there times when it is more pronounced? A growing number of literature has started to investigate this question. For example, Li and Ongena (2015), using a sample of large loans in the U.S. market, find that the certification value of bank loans is negligible prior the recent 2008 financial crisis, but then increases materially during the crisis. On the contrary, Godlewski (2014), using a sample of large loans to French borrowing firms, finds negative abnormal stock returns following bank loan announcements during the crisis. However, these studies do not examine other financial crises or differentiate between different kinds of financial crises.[3] Another important question is how bank characteristics can affect the certification value of bank loans. A number of studies have shown significant relation between abnormal stocks returns following bank loans announcements and banks' credit quality (Billet, Flannery, and Garfinkel (1995)), reputation (Johnson (1997), Ross (2010)), and origin (Ongena and Roscovan (2013)). Surprisingly, bank-borrower relationship in a context of bank loans certification value is still relatively sparsely studied, given that relationship are theorize to be a prime generator of private information (Sharpe (1990), Rajan (1992)). Moreover, recent studies have brought up the issues of competition between bank and nonbank lenders. However, the empirical evidence on how the intensity of this competition affects bank loans specialness is also still relatively scant. This paper aims to fill these gaps in the literature.

Using a novel dataset that merges 11,635 loan deals from the LPC Dealscan database and form 8-Ks from the SEC EDGAR between 1994-2014, I find that on average, only about 31% of bank loans are announced by firms. Among those loans announced, about 60% are cleanly announced and 40% are announced together with

[3] Berger and Bouwman (2013) defines two kinds of financial crises based on the origins of the crises. The crisis is classified as banking crisis if it is originated in banking industry, and market crisis if it is originated in financial markets. Other economists such as Kaminsky and Reinhart (1999) differ currency crisis as a separate kind of financial crisis, However, Berger and Bouwman's definition is more general, and currency crisis can conceptually be classified as one of the market crises since it is originated in foreign exchange market, which is part of the financial markets.

other events. Next, I find statistically and economically significant three-days Cumulative Abnormal Stock Return (CAR) following a loan announcement, which on average about +39 b.p., in line with the theory of bank loan specialness. The positive CARs are driven mainly by bank-dependent firms, which have never issued public bonds. Meanwhile, as a comparison, I show that CARs following public bond announcements by firms in the sample are negative and statistically significant. Then, using the enactment of Sarbanes-Oxley Act of 2002 (SOX) and the SEC Rule #33-8400 in 2004 as exogenous shocks to loan announcements by firms, I show significant evidence of sample selection bias in the loan announcements sample, which likely confounds the findings from the previous literature.

Being the first study that corrects the sample selection bias, using the Heckman selection method, I find that a loan is more likely to be announced during a market crisis, relative to normal times, but not during a banking crisis. Moreover, a loan is more likely to be announced by small firms and those with lower EBITDA, and when the loan has more financial covenants, is a revolver loan, has a longer maturity, secured, as well as when the firm has a previous relationship with the same lender in the past 5 years. CARs are significantly higher during a banking crisis, compared to normal times, but not in a market crisis, in line with both the asymmetric information hypothesis and the institutional memory hypothesis. In terms of loan, firm, and lender characteristics, CAR is statistically higher for a loan announced by a bank-dependent firm, and for a loan that has more financial covenants, is a revolver, and has a longer maturity, as well as a loan made by the same lender that has lent the firm in the past 5 years. Finally, I find strong evidence that CAR is negatively associated with the market share of nonbank lenders, which aligns with the competition hypothesis that explains why CARs following loan announcements shown by the recent literature, including this paper, is lower than the earlier studies have shown.

The remainder of this paper is organized as follows. Section 2.2 reviews relevant literatures and hypotheses development. Section 2.3 describes the data and methodology. Section 2.4 presents empirical results. Section 2.5 concludes.

2.2 LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Leland and Pyle (1977) contend that asymmetric information is the primary reason why financial intermediaries exist. Banks, as one form of financial intermediaries, collect funds by selling deposits and granting loans to borrowers. Specializing on this intermediation process, banks gain a cost advantage in producing and transferring information compared to arm's-length lenders. If several individual lenders grant loans directly to a borrower, there will be a duplication of monitoring effort between the individual lenders which incur higher monitoring cost. The individual lenders can reduce this cost by putting their money in a bank and delegate the tasks of monitoring loan contracts to a bank (Diamond, 1984). This "delegated monitoring" function is the key difference of banks to arm's-length lenders. In particular, banks are able to gather inside information about borrowers while arm's-length lenders can only rely on publicly available information.

According to the pecking order theory (Myers and Majluf, 1984), a firm's decision to seek for external financing may signal investors that the firm is overvalued. An external financing source with higher degree of asymmetric information is associated with higher perceived overvaluation by investors. In other words, the cost of external financing tends to increase with asymmetric information. Therefore, firms will prefer internal over external financing and when they really need external financing, they will prefer to issue debt securities over equities. Since banks specialize in information production and transmittal as well as conduct active monitoring to their borrowers, banks have less asymmetric information than other investors or lenders (Diamond, 1984, 1991). Therefore, bank loans are considered to be special and different from publicly place debt.

Most empirical evidences of bank loans specialness come from event studies of bank loan announcements. Started with the seminal paper by James (1987), using a random sample of 300 US firms over the 1974-1983 period, he finds significant evidences that bank borrowers, instead of certificates of deposit (CD) holders, bear the cost of reserve requirements on CDs. This finding is in line with Fama (1985) which contends that bank loans are special and are different than other types of privately placed and publicly placed debt. More importantly, James shows significantly positive abnormal stock returns following bank loan announcements. Lummer and McConnell (1989) assert that significantly positive abnormal stock returns following bank loans announcement are mostly attributed to bank loans renewal instead of new bank loans. Slovin, Johnson, and Glasscock (1992) show more specific evidences of bank loans specialness. They find that only small firms which show significantly positive abnormal stock returns from bank loan announcements, indicating that these firms benefit from monitoring and screening functions of banks because these firms are associated with higher degree of asymmetric information. Best and Zhang (1993) find that bank loans provide valuable informational contents, especially when the analysts' forecast errors are high. Altman, Gande, and

Saunders (2010) assert the monitoring advantage of bank loans over bonds, even when there is an active secondary market for bank loans. More specifically, they find that the secondary loan market tends to be informationally more efficient than the secondary bond market prior to a loan default.

Despite the mainstream literatures which contend that bank loan is a special type of financing which provides certification value to borrowing firms' shareholders, a strand of recent literatures attempts to challenge this view. Billet, Flannery, and Garfinkel (2006) provide evidences that bank loan announcements are associated with significant negative abnormal stock returns in the long run, suggesting that bank loans seem to be similar to other forms of external financing in the long run. Fields, Fraser, Berry, and Byers (2006) show that loan announcement abnormal returns fade away over time which might be explained by the increasing role of market-based financial system. Other studies using sample outside the U.S. loan market, such as Armitage (1995), Bailey, Huang, and Yang (2011), Godlewski, Fungacova, and Weill (2011), and Huang, Schwienbauer, and Zhao (2012) either show insignificant or negative abnormal returns following bank loan announcements. Accordingly, whether bank loans are special due to their ability to extract private information from the borrowing firms and therefore, are able to reduce the information asymmetry problem, is still an empirical research question. This "asymmetric information" hypothesis of bank loan specialness is the first hypothesis to test in this paper.

HYPOTHESIS 1: Bank loans are special due to their ability to extract private information from the borrowing firms and reduce the asymmetric information problem.

Maskara and Mullienaux (2011) shows that previous studies on bank loan announcements may not represent the loan universe since only about one-fourth of borrowing firms announce their bank loans to media. Furthermore, since the decision to announce bank loans is discretionary, the regressions of CARs following bank loan announcements will potentially suffer from self-selection bias. They show that borrowing firms with higher information asymmetry, higher prospects of cash flow problems, and material loans are more likely to announce their bank loans. Accordingly, the next hypothesis to test in this paper is:

HYPOTHESIS 2: There is a serious problem of self-selection bias in loan announcements studies.

In the model of reputation acquisition (Diamond, 1991), the monitoring function of banks benefits firms to build their reputation. More specifically, a firm with good track records on their bank loans will build a positive reputation which signals other outside investors that the firm has promising prospects. In normal times, high-rated firms do not need the benefit of bank monitoring since they already have a good reputation and revealing bad news when being caught when monitored by banks will harm their reputation. Meanwhile, very low-rated firms are rationed by banks. Therefore, during a normal time, firms with medium-rating category will benefit most from the bank monitoring function in order to build their reputation. In harsh times, such as financial crises, the need for bank monitoring will be higher since bank monitoring function is able to reduce information asymmetry. During these times, even high-rated firms will benefit from bank monitoring since it helps them to signal outside investors about their future growth opportunities. Further, bank loans may benefit borrowers due to their renegotiation features which provide more flexibility during a harsh time (Gertner and Scharfstein, 1991; Chemmanur and Fulghieri, 1994; Rajan and Winton, 1995; Cantillo and Wright, 2000; Haan and Hinloopen, 2003; Shirasu and Xu, 2007). This flexibility benefits include banks' credit lines which serve as one of liquidity sources for bank borrowers.[4] Using a sample on large-capitalization firms in Russia, Davydov and Vähämaa (2013) find that firms which rely entirely on bank debt significantly outperform firms with public debt during the recent subprime crisis. Meanwhile, Li and Ongena (2015) find significantly positive cumulative abnormal stock returns following syndicated bank loan announcements in the US market during 2005 to 2009 for both pre-crisis and crisis period. Moreover, Berger and Udell (2004) shows that in crisis times, loan officers are getting more experiences in screening loan applications, separating good and bad borrowers. On the contrary, in normal times, loan officers get less experience in doing so and therefore, this might erode their ability in screening loan applications (the institutional memory hypothesis). Therefore, we may expect that the certification value of bank loans during a financial crisis is stronger. The third hypothesis to test in this paper is:

HYPOTHESIS 3: During a period of banking crisis or market crisis, all else equal, borrowing firms are more likely to announce their bank loans compared to normal times.

Although bank loans may benefit firms, especially during a harsh time, several studies show that dependency on bank loans can harm borrowing firms. Theoretically,

[4] Ivashina and Scharfstein (2010) show evidences that firms drew down their credit lines more extensive during the recent subprime crisis. Campello, Giambona, and Graham (2011) find similar findings which show that credit lines eased the impact of the financial crisis on firm spending. However, Sufi (2009) asserts that bank lines of credit or revolving credit facilities, are viable as a liquidity source only for those borrowers that maintain high cash flow.

adverse selection and moral hazard problems hinder a firm to be able to easily access external capital markets or switch between different sources of external financing (Holmstrom and Tirole, 1997). Accordingly, a firm's performance may be sensitive to the shocks occurred to its external financing sources. When there is a negative shock affecting banks' performance which significantly reduces their ability to provide loans supply, this shock may propagate to bank-dependent borrowers. During this period, banks will tend to impose tighter covenants, reduce their new loans, and increase interest rate. Kang and Stulz (2000) provide evidences from the Japan's financial crisis during 1990-1993 and find that firms with higher fraction of bank loans perform worse and invest less. Chava and Purnanandam (2011) provide evidences from the 1998 Russian crisis that bank-dependent firms suffer from larger valuation losses as well as decline in capital expenditure and profitability, relative to firms which rely on public-debt market. Using a sample of large loans to French borrowing firms during the 2000's boom and bust periods, Godlewski (2014) finds no significant stock market reactions to bank loan announcements during the boom period and significant negative reactions during the bust period. In summary, whether bank loans provide certification value during normal times and financial crises remains inconclusive. The fourth hypothesis to test is:

HYPOTHESIS 4: During a period of banking crisis or market crisis, all else equal, abnormal stock returns following bank loan announcements are higher than normal time.

2.3 DATA AND METHODOLOGY

2.3.1 LOAN POPULATION

I start from the population of U.S. denominated loan deals from the Dealscan database from 1994-2014.[5] This period includes two market crises and one banking crisis. Berger and Bouwman (2013) define a market crisis as a financial crisis that originates from the financial markets, while a banking crisis is a financial crisis that originates from the banking industry. The market crises are the Russian debt crisis and Long-Term Capital Management (LTCM) bailout (1998:Q3-1998:Q4), and the dotcom bubble and the September 11th terrorist attacks (2000:Q2-2002:Q3). While the banking crisis is the recent subprime crisis (2007:Q3-2009:Q4). All periods other than these crises are normal times.

I filter the loans by including only the U.S. borrowing firms. Following the common practice in the literature, I start with excluding borrowers categorized as financial firms, utilities firms, and government institutions.[6] Then, I exclude loans with the deal purpose of “Takeover”, "LBO", "Stock buyback", "Spinoff", "Dividend Recap", "ESOP", "IPO Relat. Finan.", "SBO", "Merger", "MBO" as if a borrowing firm announces any of these loans, it is unclear whether the subsequent firm’s shareholders reaction (if any) is due to the loan announcement itself or due to the information about the purpose of the loan. Further, events such as takeover, merger, and acquisition commonly have a long period of information leakage and further details revelation (e.g.

[5] I start from 1994 as this is the earliest coverage that is available in the directEDGAR, a software platform that I use to scrape 8-Ks from the SEC EDGAR website.

[6] Financial firms are those with *PrimarySICCode* between 6000 and 6999. Utilities firms are those with *PrimarySICCode* between 4910 and 4940. Government institutions are those with *PrimarySICCode* between 9100 and 9999. To make sure that financial firms are excluded, I conduct a further filtering by dropping any loan deal having *InstitutionType* that contains at least one of the following terms: “bank”, “finance”, “financial”, “investment”, “insurance”, “thrift”, “S&L”, “fund”, “pension”, “mortgage”, “invest”, “hedge”, or “trust”.

Degryse, Kim, and Ongena, 2009). Therefore, the short run event study methodology, which has become the standard methodology to test bank loan specialness, is not suitable to apply to these events. I also exclude loans with the deal purpose of "Coll. Debt Oblig. (CDO)" and "Undisclosed".

To get financial information on borrowing firms and lenders, I merge the loan deals dataset with Compustat.[7] Following the standard approach in the literature, I drop firms having total assets less than $1 million or missing market value of equities. As loans from the Dealscan commonly have multiple lenders, following the common practice in the previous literature, I focus only on the lead lenders as they are the main repository of private information (e.g. Sufi, 2007; Bharath, Dahiya, Saunders, and Srinivasan, 2007; Balasubramanyan, Berger, and Koepke, 2017). A lender is defined as the lead lender if LeadArrangerCredit = "Yes" in the Dealscan database. Then, I complement this with the definition from Dahiya, Saunders, and Srinivasan (2003), which defines lead lenders as those having lender role as “arranger”, “administrative agent”, “agent”, or “lead bank”. If there are multiple lead lenders, I choose the one with the highest lending relationship intensity in the past 5 years, following Bharath, Dahiya, Saunders, and Srinivasan (2011). If there are still multiple lead lenders left after these filtering processes, I choose the one with the largest bank allocation and total assets.

Finally, I merge the dataset with CRSP to get the stock prices information. So far, the filtering and merging processes result in 11,678 loan deals or 15,838 loan facilities. Then, following Brown and Warner (1985), a firm must have at least 30 daily returns in

[7] I start from the Dealscan-Compustat linktables provided by Michael Roberts (Chava and Roberts, 2008) and Michael Schwert (Schwert, JF forthcoming). Then, I update these links using the bigram fuzzy matching algorithm similar to Chodorow-Reich (2014) and retains all firm matches with matching score greater than 0.98. Finally, I inspect manually each of the firm match with matching score less than 1 but greater than 0.98, and keep the correct matches only.

the entire estimation period of the event study on loan announcement and no missing return in the last 20 days before the loan announcement event.[8] This filter drops another 43 deals, which results in a final 11,635 loan deals or 15,776 loan facilities. Figure 2.1 plots the number and amount of loan deals included in this study for each year from 1994-2014. From the figure, we can see that the greatest decline in number and amount of loan deals occurred during the subprime crisis. Post the subprime crisis, the number and amount of loan deals have been gradually increasing back with a peak in year 2011, which was driven by refinancing loans (Thomson Reuters, 2011).

2.3.2 LOAN ANNOUNCEMENTS

To provide investors with current information of material corporate events, the SEC mandates publicly listed firms to notify investors via the Form 8-K.[9] However, the SEC does not specifically requires firms to inform investors about bank loans, different than the issuance of any arm's length public debts or equities. Accordingly, a bank loan disclosure via the Form 8-K is mostly voluntary (Maskara and Mullineaux, 2011). This discretionary feature of bank loan announcements via 8-Ks is similar to the feature of loan announcements through the media, in which most of the previous literature on bank loan specialness relies on.

However, there are at least three reasons why bank loan announcements through the 8-Ks are more superior to test bank loan specialness compared to those through the news media. First, a loan announcement in the media in most cases is short due to limited spaces, meanwhile, a loan announcement in 8-K in most cases is supplemented by the

[8] More detailed methodology of the event study following a loan announcement will be explained in Section 2.4.3 and 2.4.4.
[9] SEC Staff Accounting Bulletin No. 99—Materiality.

complete loan contract, and therefore, provides more information about the loan. Second, there is some evidence that media self-select the loan announcements, in which the news editors make subjective judgments about what is newsworthy (Preece and Mullineaux, 1994). There is also some evidence that news editors may push only positive news stories (Lummer and McConnel, 1989; Fery, Gasbarro, Woodliff, and Zumwalt, 2003). Accordingly, most of the previous studies that rely on bank loan announcement samples from the media not only faces the self-selection bias from the discretionary feature of loan announcements by the borrowing firms, but also the self-selection bias from the news editors. Third, from the 8-K loan announcements that I observed, borrowing firms also inform to the investors about any disclosure made in news media about the loans, which most cases are on the same date as the 8-Ks or after. Nevertheless, it is still possible that a loan is announced in the media before the 8-K date, and in this case, we might underestimate the abnormal stock returns following loan announcements. But, as more detail information about the loans are made in 8-Ks, not in the media, we might expect that the major portion of investors reaction occurs following the 8-K announcements.

To search for loan announcements in 8-Ks, I scrape the SEC's EDGAR website using the directEDGAR, a software platform that enables users to search, extract, and normalize contents from the SEC EDGAR filings.[10] Since the 8-K library in the directEDGAR starts from 1994, the sample of loan announcements in this paper follows. For all 11,635 filtered loan deal observations explained in Section 4.1, I search their respective loan announcements in 8-Ks via the directEDGAR using the following search terms and booleans: line of credit OR credit line OR credit facility OR credit agreement

[10] http://directedgar.com/

OR credit extension OR new loan OR loan agreement OR loan renewal OR loan revision OR loan extension OR term loan OR revolver OR commercial loan OR bank loan OR syndicated loan. The search terms are based on Billet, Flannery, and Garfinkel (1995).

On March 25, 2004, the SEC had released the Rule #33-8400, which would be effective starting on August 23, 2004. This rule is a follow up to the "real time issuer disclosure" mandate in Section 409 of the Sarbanes-Oxley (SOX) Act of 2002.[11] The Rule #33-8400 makes two major changes in 8-K filings. First, it expands and reorganizes the Form 8-K, adding eight more new items. Under this new rule, disclosures about a bank loan financing (if the borrowing firm decides to do so) is classified as Item 1.01—Entry into a Material Definitive Agreement. Prior to this rule, the voluntary bank loan disclosures were classified as Item 5—Other Events, which under the new rule is classified as Item 8.01—Other Events. Second, the SEC accelerates the Form 8-K filing deadline into a maximum of four business days following the occurrence of the event disclosed. Prior to this rule, the filing deadline was five to fifteen business days after the disclosed event's occurrence date.

Using the search terms and booleans as mentioned above, the directEDGAR produces a summary extraction table, which gives the number of word hits on each search term and from which 8-K Items the hits are found. As the directEDGAR has mapped the old Items classification to the new Items classification under the Rule #33-8400, from hereafter, Form 8-K Items discussed refer to the new Items classification. To identify loan announcements in 8-Ks from the summary extraction table, I employ the following strategies.

[11] The SEC Rule #33-8400 can be accessed at https://www.sec.gov/rules/final/33-8400.htm.

First, as prior to the Rule #33-8400 voluntary loan announcements were classified as other events, for all loans with deal active dates before August 23, 2004, I identify a loan as announced in 8-K when there are positive word hits from any of the search terms that are from Item 8.01—Other Events. A loan is "cleanly" announced, without any other confounding events, when there are no hits from other 8-K Items other than the Item 8.01. With the exception of Item 2.03—Creation of a Direct Financial Obligation or an Obligation under an Off-Balance Sheet Arrangement of a Registrant, Item 2.04—Triggering Events that Accelerate or Increase a Direct Financial Obligation under an Off-Balance Sheet Arrangement. Conditional on a loan is announced, these Items mostly contain additional information related to the loan. Other Items excepted are Item 3.03—Material Modification to Rights of Security Holders, which conditional on a loan is announced mostly contains of information about financial covenants; Item 7.01—Regulation FD, which contains the declaration of fair disclosure; and Item 9.01—Exhibits, which conditional on a loan is announced contains the complete loan contract. If a loan is identified as announced using the Item 8.01 filter but there are positive word hits from Items other than the Items in the exception, I classified the loan announcement as "contaminated".[12]

Second, post the Rule #33-8400, for all loans with deal active dates on August 23, 2004, and after, I identify a loan as announced in 8-K when there are positive word hits from any of the search terms that are from Item 1.01—Entry into a Material Definitive Agreement. A loan is "cleanly" announced, without any other confounding events, when there are no hits from other 8-K Items other than the Item 1.01 and excepted Items from

[12] The most frequent confounding events are from the Item 2.02—Results of Operations and Financial Condition, which are either quarterly or annual earnings announcements.

the first strategy. If the loan is identified as announced using the Item 1.01 filter but there are positive word hits from Items other than the Items in the exception, I classified the loan announcement as "contaminated". It is important to note that after the Items reclassification mandated by the Rule #33-8400, any positive words hit that are from the Item 8.01 most of the time contains confounding events to the loan announcement, e.g. selling of subsidiaries, etc.

These strategies result in 3,613 loan announcements, which consist of 2,172 clean loan announcements, and 1,441 contaminated loan announcements. Finally, I randomly choose 1,500 from the 3,613 loan announcements to inspect manually, and confirm the accuracy of the loan announcement filtering strategies. The rest 8,022 of the filtered loans from Dealscan that do not find match on 8-Ks are classified as "unannounced" loans. Table 2.1 summarizes the results.

We can see from the table that in overall, about 31% of loans are announced, and among those announced, about 60% are cleanly announced. The SOX Act of 2002 aims to protect investors by improving the accuracy and reliability of corporate disclosures.[13] Prior to the SOX, the percentage of loans announced in 8-K was relatively low, which was about 5%. However, post the SOX, the relative percentage doubled to almost 12%. The more material increase in relative percentage of 8-K loan announcements occurred after the enactment of the Rule #33-8400, which climbed to about 56%. These suggest that both of the SOX and Rule #33-8400 seem to have successfully endorsed more loan announcements via 8-Ks, as a part of the increase in the firms' disclosure to their investors.

[13] The SOX Act of 2002 can be accessed at https://www.sec.gov/about/laws/soa2002.pdf.

Figure 2.2 shows the trend of loan announcements over time from 1994-2014. From the figure, we can see sharp increases in relative loan announcement percentage post the SOX and Rule #33-8400. We can also see some positive trends in relative loan announcement percentage during the market and banking crisis periods.

2.3.3 EVENT STUDY METHODOLOGY

Event studies have been extensively used in the literature to examine the information content of corporate events. The traditional event study methodology, developed by Fama, Fisher, Jensen, and Roll (1969), contends that if a corporate event has an information effect, we should observe a nonzero stock-return reaction on the event date. The use of the event study methodology to test the information effect following a bank loan announcement is started by James (1987), which then spawns the long-standing empirical literature on bank loans specialness. The event study set up used in this paper is as follow.

First, the event date used for each loan announced in 8-K is the filing date. In most cases, the filing date is the same as the deal active date. As the new 8-K filing deadline under the Rule #33-8400 is a maximum of four business days following the occurrence of the event disclosed, some loan announcements after 2004 are made around this range. Before 2004, the filing dates can range from the deal active date to fifteen days after. Next, for each "clean" loan announcement, I run a daily stock return benchmark model. Following most of the previous literature, I use the market model as the baseline. For robustness checks, I use the Fama-French 3 Factors (Fama and French, 1993) and the Fama-French 5 Factors (Fama and French, 2015) as alternative benchmark models. I follow Billet, Flannery, and Garfinkel (1995) to use an estimation window over the period [-200, -51] and require a minimum of 30 daily non-missing stock returns for the entire estimation and no missing return in the last 20 days before the loan announcement event, following Brown and Warner (1985).

Then, I compute the abnormal stock return around a loan announcement by firm j at event date t using each of the benchmark models as follows.

$$AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{mt}) \tag{1}$$

$$AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j (R_{mt} - R_{Ft}) + \hat{\gamma}_j SMB_t + \hat{\delta} HML_t) \tag{2}$$

$$AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j (R_{mt} - R_{Ft}) + \hat{\gamma}_j SMB_t^* + \hat{\delta} HML_t + \hat{\epsilon}_j RMW_t + \hat{\phi}_j CMA_t) \tag{3}$$

where AR_{jt} is the abnormal stock return at event date t, R_{jt} is the stock return, R_{mt} is the market return proxied by the value-weighted CRSP index return, R_{Ft} is the risk-free rate proxied by the one-month Treasury bill rate, SMB_t is the average return on the three small portfolios minus the average return on the three big portfolios, SMB_t^* is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios, HML_t is the average return on the two value portfolios minus the average return on the two growth portfolios, and CMA_t is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios. $\hat{\alpha}_j$, $\hat{\beta}_j$, $\hat{\gamma}_j$, $\hat{\delta}$, $\hat{\epsilon}_j$, and $\hat{\phi}_j$ are parameter estimates for each benchmark model over the estimation window.

Next, the Cumulative Abnormal Returns (CARs) for firm j that announce loan i within an event window from time t_1 to t_2 is computed as follow.

$$CAR_{ij,t_1,t_2} = \sum_{t=t_1}^{t_2} AR_{ij,t} \tag{4}$$

To capture how abnormal returns behave around a loan announcement date, I calculate seven different event windows: [-2,+2], [-1,+1], [0,+2], [0,+1], [0,0], [-1,0], and [-2,0]. Further, we aggregate the CARs cross-sectionally among all loan announcements to compute the Cumulative Average Abnormal Returns (CAARs) for each event window with the following formula.

$$CAAR_{ij,t_1,t_2} = \frac{1}{N} \sum_{\forall ij} CAR_{ij,t_1,t_2} \tag{5}$$

where N is the number of all loan announcements. Lastly, we test whether CAAR for each event window is statistically different than zero (H_0: $CAAR = 0$) using three different statistics: Patell-Z statistic (Patell, 1976), the Cross-Sectional test statistic (CS-t), and the Standardized Cross-Sectional test statistic (BMP-t) as in Boehmer, Musumeci, and Poulsen (1991).[14] Following the concensus in the literature of bank loan specialness, if the null hypothesis is rejected statistically and CAAR is positive, we can conclude that bank loans are special.

2.3.4 CORRECTION FOR SELF-SELECTION BIAS

Event studies are commonly followed by a linear regression of the abnormal stock returns on a set of explanatory variables. However, announcement of bank loans by the borrowing firms, similar with many other corporate events, are discretionary non-random events. Fery, Gasbarro, Woodliff, and Zumwalt (2003) and Maskara and Mullineaux

[14] Among these three statistics, BMP-t is robust to event-induced volatility and accounts for serial correlation.

(2011) are the first papers that brought up this issue. Using the data from publicly listed firms in Australia from 1983-1999, Fery, Gasbarro, Woodliff, and Zumwalt find significant positive abnormal stock returns following loans published in the financial press, but find no significant reaction for those non-published loans. Maskara and Mullineaux examine the self-selection issue more comprehensively. Using the data of loans to U.S. borrowing firms from the Dealscan between 1987 and 2004, their findings suggest that the previous studies relying on loan announcements sample from the media likely suffer from a self-selection bias due to the rare nature of loan announcements by borrowing firms. Accordingly, any study that examines factors affecting abnormal stock returns post loan announcements should take into account this self-selection bias. Surprisingly, there is no paper yet that I am aware of has done such effort. Several latest papers such as Gande and Saunders (2012) and Li and Ongena (2015) instead advocate a strong assumption that all loans from the Dealscan are announced at their active date to avoid the potential self-selection bias. However, this might not be a realistic assumption as we can see from Table 2.1 that only about 31% of the Dealscan loans are announced in 8-Ks.

To address the self-selection bias in loan announcements by the borrowing firms, I use the conditional event study methodology, which applies the Heckman selection model (Heckman, 1979) in the context of an event study (e.g. Acharya, 1988, 1993; Eckbo, Maksimovic, and Williams, 1990; Nayak and Prabhala, 2001). Applying to the bank loan announcement study, we have the following *CAR* equation to be estimated:[15]

$$CAR^{*} = \boldsymbol{x_j}\boldsymbol{\beta} + \nu_{1j} \qquad (6)$$

[15] Indexes are suppressed for brevity.

where $\boldsymbol{x_j}$ is a vector of independent variables affecting CAR, including borrowing firms characteristics, loan characteristics, lender characteristics, market crisis and banking crisis indicators, and market share of nonbank lenders, $\boldsymbol{\beta}$ is a vector of coefficient estimates, and ν_{1j} is the error term of the regression equation. Since we observe CAR^* only if a loan is cleanly announced in 8-K, we also have a selection equation as follow.

$$L^* = \boldsymbol{z_j\gamma} + \nu_{2j} > 0 \tag{7}$$

where $\boldsymbol{z_j}$ is a vector of instrument variables and controls affecting clean loan announcement (L^*), and ν_{2j} is the error term of the selection equation. If the selection bias matters, the correlation between ν_{1j} and ν_{2j} (ρ) would be statistically different than zero. The selection equation is estimated using a probit regression. Meanwhile, the CAR equation is estimated using the Heckman selection model, which are based on Heckman (1979) with applying a maximum-likelihood procedure (Maddala, 1983). Ross (2010) advocates this method instead of the traditional two-step procedure to address the heteroscedasticity in abnormal returns.

The instrument variables for the selection equation are SOX_REG that equals 1 for loans having deal active date post the Sarbanes-Oxley enactment (July 2002 onward) and 0 otherwise, and 8K_REG that equals to 1 for loans having deal active date post the effective date of the SEC Rule #33-8400 (August 2004 onward) and 0 otherwise. These government regulations provide exogenous shocks to the level of publicly listed firms' information disclosure, and therefore, to loan announcements via 8-Ks.

2.4 EMPIRICAL RESULTS

2.4.1 LOAN, BORROWING FIRMS, AND LENDER CHARACTERISTICS

As shown in Table 2.2, this paper covers 11,635 loan deals from the Dealscan from 1994-2014. The average loan deal size is $549 million with about 8 lenders participating on average. About 72 percent of the loans are revolvers, and about 7 percent are term loans. The rest of the loans are either combination between revolvers and term loans or other type of loans. The average maturity of the loans is 48 months, and about 46 percent are secured. Moreover, some loans are without any type of financial covenants, and some others have financial covenants up to seven different types of financial covenants.

In terms of borrowing firm characteristics, the average total size of the firms is about $6.9 billion. The smallest firm has total assets about $2 million, and the largest one has about $798 billion total assets. The firms have average Tobin Q of 1.75, market leverage of 41 percent, EBITDA-to-assets ratio of 12 percent, and information asymmetry index of 2.60. Moreover, about 58 percent of the firms have never issued public bonds during the sample period, and about 51 percent have no long-term or short-term issuer credit ratings.

The lead lenders have total assets about $898 billion on average. The smallest lead lender has total assets about $992 million, while the largest one has about $2,416 billion. The average capitalization ratio of the lead lenders is about 8 percent, and about 69 percent are the big three market leaders in the loan market. About 31 percent of lead lenders have previous lending relationship with the borrowing firms over the past 5 years.

Finally, nonbank lenders are only about 3 percent on average, and their average market share is about 2 percent.

2.4.2 ARE BANK LOANS STILL SPECIAL?

Table 2.3 shows the Cumulative Average Abnormal Returns (CAARs) following 8-K clean loan announcements. In Panel A, we can see that CAARs following loan announcements are positive and statistically significant in event window [0,+1], [0,+2], [-1,+1], and [-2,+2]. The results are robust using three different benchmark models and different type of test statistics. Interestingly, none of the CAAR in event window [-1,0], and [-2,0] are statistically significant.[16] This finding suggests that there is no information leakage for cleanly announced loans before the announcement dates in 8-Ks, suggesting that the announcement does have information content for the investors. If we observe statistically significant CAARs prior to date 0, this means that investors can somehow get early information about the loans from other sources other than the 8-Ks, and therefore, the information content in the 8-K is less valuable to the investors. This is in line with the asymmetric information hypothesis. The one-day CAAR at [0,0] is also not statistically significant. This lends a support to the notion that it takes more time for the investors to process the information in 8-K as it contains a more detailed information than announcements in news media. Maybe an investor reads the loan contract attached in the 8-K thoroughly after it is announced, and then her reaction the next days will depend on

[16] Using the market model, BMP-t and Patell-Z are statistically significant for the event window [-2,0]. However, they are only marginally significant, and the significance disappear once we add other factors such as SMB and HML in the Fama-French 3 factors model and SMB, HML, RMW, and CMA in the Fama-French 5 factors model.

whether she perceives the loan as bad or good news. Therefore, the evidence so far suggests that bank loans are still special.

Panel B of Table 2.3, which presents CAARs for contaminated loan announcements, shows a similar pattern with Panel A. In terms of magnitude, CAARs for these loans are relatively higher than cleanly announced loans. As these loans are announced together with other events, the total information contents of these loans will depend on the confounding events. However, some studies have shown that loan announcements are generally pushed as positive news (Lummer and McConnel, 1989; Fery, Gasbarro, Woodliff, and Zumwalt, 2003), and therefore, we may expect that if a loan is announced together with other events, those events are likely to be positive or at least neutral events.

Panel C of Table 2.3 presents CAARs for unannounced loans. Using the loan active date as the event date, similar with Gande and Saunders (2012) and Li and Ongena (2015), we can see that CAARs for these loans are still positive and statistically significant, though the magnitudes are relatively lower compared to Panel A and B. Different than announced loans, Panel C shows some evidence of information leakage prior to the loan active date. This finding suggests that investors might be able to get some private information about the borrowing firms without having to rely on loan announcements in 8-K. In other words, the borrowing firms of these loans might not suffer serious information asymmetry problem, and therefore they do not need to announce their loans to convey positive signals about the firms' conditions to their investors. This finding is also parallel with the asymmetric information hypothesis.

Panel D of Table 2.3 presents a further investigation on CAARs following the deal active date of unannounced loans. The panel shows that for deals that consist only revolver loans, there are no statistically significant CAARs following deal active date. Compared with the results on Panel C, this indicates that the positive and statistically significant CAARs following the deal active date of unannounced loans are mainly driven by the inclusion of term loans in the deals.[17] Drucker and Puri (2009) show that term loans are more likely to be sold in the secondary markets compared to revolver loans (credit lines).[18] Bruche, Malherbe, and Meisenzahl (2017) show that during a term loan syndication process prior to the secondary market, there is a period of primary market book-running before the loan active date in which potential institutional investors get information about the loan from the lead arranger. Accordingly, it could be that the positive CAARs around the deal active date for term loans that are unannounced in 8-Ks capture the institutional investors' reaction to the information they get during the book-running period. This is consistent with Gande and Saunders (2012), which find positive investor reactions on loans traded in the secondary market.

In Table 2.4, I compute CAARs separately between bank-dependent and nonbank-dependent firms. I define bank-dependent firms as those that never issue public bonds during the sample period from 1994-2014.[19] As these firms have never issue public bonds, they are more likely to suffer from material asymmetric information problem. If bank loans are special and convey positive signals from the banks' certification values

[17] Other loans also show similar results with deals that include term loans. However, the number of other loans in the sample is much less than term loans.

[18] Drucker and Puri show that term loans composing of 64% of the loans sold, compared to revolver loans that only comprise of 24% of the loans sold.

[19] Technically, to identify these firms, I merge the filtered Dealscan data with FISD. Firms that are in the Dealscan but not in the FISD during the sample period are defined as bank-dependent firms.

due to their ability to reduce information asymmetry problem, we would expect that CAARs are positive and statistically significant on bank-dependent firms. On the contrary, CAARs would be less or not statistically significant for nonbank-dependent firms. These are exactly what I find in Panel A and B of Table 2.4. Again, this finding supports the asymmetric information hypothesis and aligns with the notion that bank loans are special because of the banks' certification function that is able to reduce information asymmetry problem.

Lastly, as comparison, I conduct an event study on public bonds issued by the borrowing firms from the filtered Dealscan database. As public issues of debt or equity must be disclosed through the registration process, I use the public bond offering dates in FISD database as the announcement dates. Similar with the early findings such as James (1987), I find negative CAARs following announcements of public bond issuances. The results are shown in Table 2.5.

2.4.3 FACTORS AFFECTING LOAN ANNOUNCEMENTS

The next analysis is to identify what factors affecting borrowing firms to announce their loans in 8-K. Before doing so, I check the Variance Inflation Factors (VIFs) of all regressors to make sure that there is no serious multicollinearity problem. As shown in Table 2.6, there is no evidence of excessive multicollinearity between the regressors (i.e. no VIFs greater than 20, the suggested threshold as in Greene, 2012).

Table 2.7 presents the probit regression results of "clean" loan announcements on the instrument variables and other relevant regressors. The instruments, SOX_REG and 8K_REG are statistically significant on all probit specifications from column (1) to (5), controlling for borrowing firms, loans, and lender characteristics. The results are robust if we use logit instead of probit in column (6). In terms of marginal impacts, a loan is more likely to be cleanly announced by 23% post the SEC Rule #33-8400, and by 6% post the SOX. Compared to the relative percentage of clean loan announcement in overall (18.67%, Table 2.1), these marginal impacts are economically material. This suggests that both variables are relevant instruments for clean loan announcements. Next, I find that a clean loan announcement is more likely by 4% during a market crisis compared to normal times. This aligns with the asymmetric information hypothesis. However, there is no evidence that loans are more likely to be cleanly announced during a banking crisis compared to normal times. One plausible explanation is that during a banking crisis, the information asymmetry problem is more severe for banks (lenders) than for the borrowing firms. Meanwhile, during a market crisis, it is the other way around.

In terms of borrowing firm characteristics, there is some evidence that small borrowing firms and those with lower EBITDA ratio are more likely to cleanly announce their loans, which lends a support to the asymmetric information hypothesis. Loan characteristics seem to be stronger determinants of clean loan announcements. In particular, a loan is more likely to be cleanly announced when it has more financial covenants, is a revolver, has longer maturity, and is secured. Lastly, a loan is more likely to be cleanly announced when the lender has a previous lending relationship with the borrowing firms in past 5 years, when the lender has higher capital, larger size, and is a nonbank lender.

Table 2.8 presents the probit regression results of "contaminated" loan announcements on the instrument variables and other relevant regressors. REG_8K is still relevant statistically to explain the likelihood of contaminated loan announcements, but SOX is not. There is no evidence that these loans are more likely to announce during a market crisis, and only weak evidence that these loans are less likely to announce during a banking crisis, relative to normal times. Next, a loan is more likely to be announced together with other events if the borrowing firm is a small borrower, as well as if the loan has more financial covenants and longer maturity. Revolvers and term loans are both less likely to be announced with other events. This suggests that contaminated loan announcements are driven by other loan types. Similar with clean loan announcements, a loan is more likely to be announced with other events if the lender has more capital and is a nonbank lender. Interestingly, a loan is more likely to be announced with other events if it is a new loan, i.e. the lender has no previous lending relationship with the borrowing firm.

2.4.4 FACTORS AFFECTING CARS FOLLOWING LOAN ANNOUNCEMENT

Table 2.9 presents the regression estimates of CARs following clean loan announcements on a variety of determinants, including market and banking crisis, as well as borrowing firm, loan, and lender characteristics. As we have seen from Table 2.3 that the information leakage prior to a clean announcement is less likely, I use CAR [0,+1] and CAR[0,+2] as the dependent variables in the second step of the conditional event study. Regression coefficients in column (1) are estimated using OLS without correcting for the sample selection bias. The rest of the columns are estimated using the Heckman selection model, which are based on Heckman (1979) using a maximum-likelihood procedure (Maddala, 1983). As we can see from Table 2.9, the Inverse Mills ratio from the Heckman model is statistically significant at 99% confidence level in all specifications, controlling for stock price runup, market and banking crisis, and a variety of borrowing firm, loan, and lender characteristics, as well as industry and year fixed effects. This finding suggests a significant evidence of a serious self-selection bias, and therefore, a correction is needed to mitigate this bias using the Heckman models.

Next, CARs are significantly higher during a banking crisis, compared to normal times, but not in a market crisis, in line with both the asymmetric information hypothesis and the institutional memory hypothesis. In terms of borrowing firm characteristics, I find strong evidence that positive CARs following loan announcements are driven by bank-dependent firms, and some evidence of that positive CARs are attributed to borrowing firms with lower EBITDA ratio. Both findings are consistent with the asymmetric information hypothesis. Moreover, I find that a loan with more financial covenants is strongly and positively associated with CARs following a clean announcement. In the meantime, there is also some evidence that a loan that is a revolver, has longer maturity, and made by a lender with previous lending relationship is associated positively with CARs following a clean loan announcement. Lastly, I find strong evidence that CARs are negatively associated with the market share of nonbank lenders, which aligns with the competition hypothesis that explains why CARs following loan announcements are not as high as the earlier studies have shown.

2.4.5 ADDITIONAL ROBUSTNESS CHECKS

As additional robustness checks, Table 2.10 provides the Heckman regression results using the Buy-Hold-Abnormal Returns (BHAR) and raw return as the dependent variables instead of CAR. The table shows similar results with our main results from Table 2.9.

2.5 CONCLUSION

This paper provides empirical evidence of the certification value of bank loans from the U.S. market in the last two decades, which has experienced both market crisis and banking crisis. Using a novel dataset that merges loan deals from the Dealscan database and form 8-Ks from the SEC EDGAR between 1994-2014, I find that on average, only about 31% of bank loans are announced by firms. Among those loans announced, about 60% are cleanly announced and 40% are announced together with other events. Next, I find statistically and economically significant three-days Cumulative Abnormal Stock Return (CAR) following a loan announcement, which on average about +39 b.p., in line with the theory of bank loan specialness. The positive CARs are driven mainly by bank-dependent firms, which have never issued public bonds. Meanwhile, as a comparison, I show that three-days CARs following public bond announcements by firms in the sample are negative and statistically significant.

Then, using the enactment of Sarbanes-Oxley Act of 2002 (SOX) and the SEC Rule #33-8400 in 2004 as exogenous shocks to loan announcements by firms, I show significant evidence of sample selection bias in the loan announcements sample, which likely confounds the findings from the previous literature. Being the first study that corrects the sample selection bias, using the Heckman selection method, I find that a loan is more likely to be announced during a market crisis, relative to normal times, consistent with the asymmetric information hypothesis. Moreover, a loan is more likely to be announced by small firms, firms having lower EBITDA, and when the loan has more financial covenants, is a revolver loan, has a longer maturity, secured, as well as when the firm has a previous relationship with the same lead lender in the past 5 years and when the lead lender has higher capital, larger size, and is a nonbank.

Then, I find that the CARs are significantly higher during a banking crisis, compared to normal times, but not in a market crisis, in line with both the asymmetric information hypothesis and the institutional memory hypothesis. In terms of loan, firm, and lender characteristics, CAR is statistically higher for a loan announced by a bank-dependent firm, a firm with lower EBITDA ratio, and for a loan that has more financial covenants, is a revolver, and has a longer maturity, as well as a loan made by the same lender that has lent the firm in the past 5 years. Finally, I find strong evidence that CAR is negatively associated with the market share of nonbank lenders, which aligns with the competition hypothesis that explains why CARs following loan announcements shown by the recent literature, including this paper, is not as high as the earlier studies have shown.

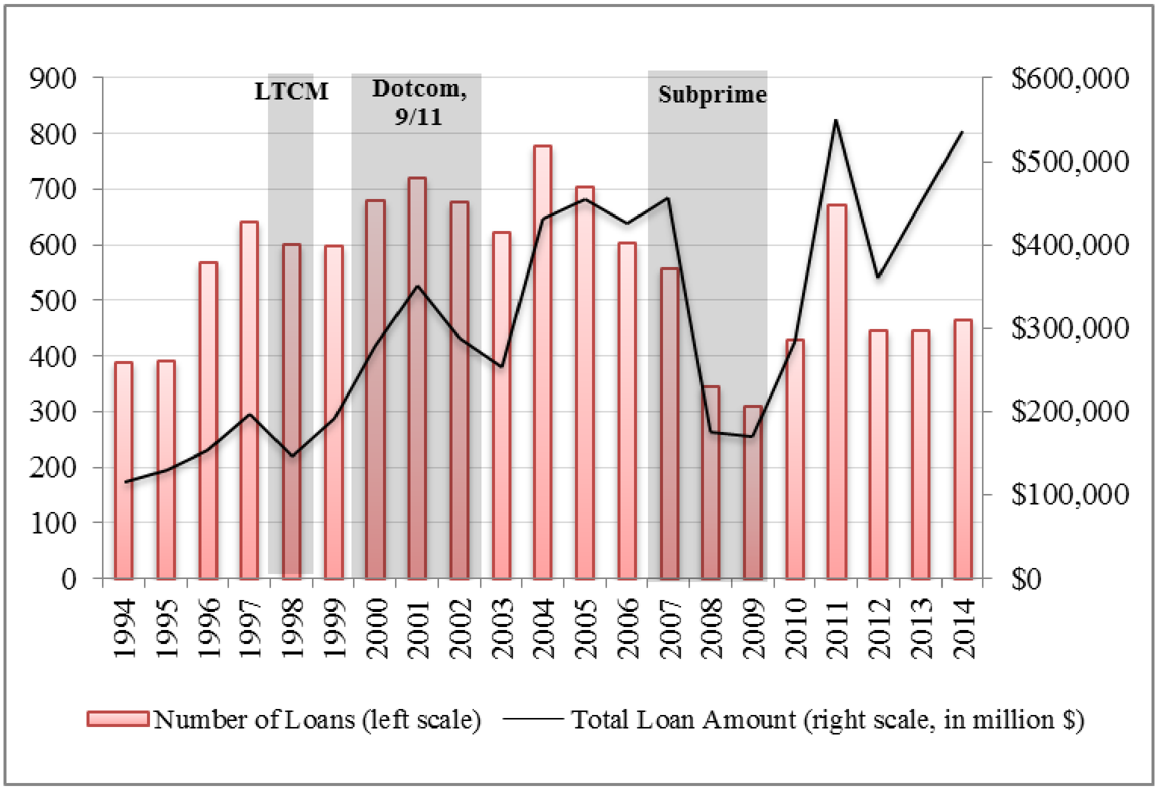

Figure 2.1: Number and Amount of Loan Deals from 1994-2014

This figure plots the number and total amount of loan deals from the Dealscan from 1994-2014. The number of loans is shown in the left scale, while the dollar amount of loans (in million $) is shown in the right scale. The first shaded area shows a period when the Russian debt crisis and the LTCM bailout occurred. The next shaded area is a period when the dotcom bubble and the 9/11 crisis occurred. And the last shaded area is when the recent subprime mortgage crisis occurred.

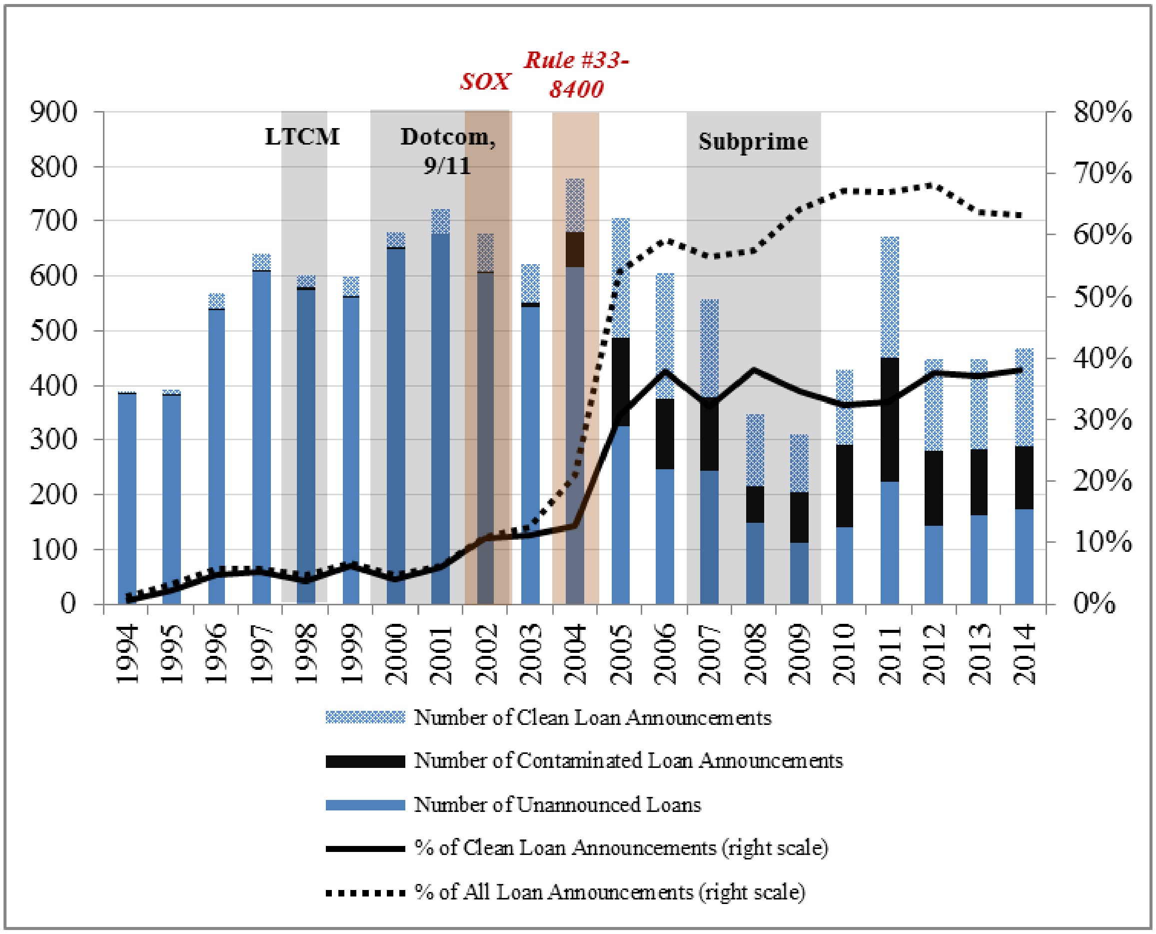

Figure 2.2: Loan Announcements from 1994-2014

This figure plots the number and percentage of loans announced in 8-Ks from 1994-2014. The number of loan announcements is shown in the left scale, while the percentage of loans announced is shown in the right scale. The first grey shaded area shows a period when the Russian debt crisis and the LTCM bailout occurred. The next grey shaded area is a period when the dotcom bubble and the 9/11 crisis occurred. And the last grey shaded area is when the recent subprime mortgage crisis occurred. The two orange shaded areas show the year when the Sarbanes-Oxley Act and the SEC amendment of Rule 308 were enacted respectively.

Table 2.1: Loan Announcements Pre and Post the SOX and SEC Rule #33-8400

This table shows the number and percentage of loans announced in 8-Ks from 1994-2014 pre and post the Sarbanes-Oxley Act of 2002 (SOX) and the SEC Rule #33-8400 of 2004.

	Overall (1994-2014)	Pre SOX of 2002	Post SOX, pre SEC Rule #33-8400 of 2004	Post SEC Rule #33-8400 of 2004
Number of Loans	11,635	4,587	1,298	5,750
Number of Unannounced Loans	8,022	4,356	1,145	2,521
Number of Loan Announcements	3,613	231	153	3,229
Number of Clean Loan Announcements	2,172	202	142	1,828
Number of Contaminated Loan Announcements	1,441	29	11	1,401
% of Loan Announcements to All Loans	31.05%	5.04%	11.79%	56.16%
% of Clean Announcements to All Loans	18.67%	4.40%	10.94%	31.79%
% of Contaminated Announcements to All Loans	12.39%	0.63%	0.85%	24.37%
% of Clean Announcements to All Announced Loans	60.12%	87.45%	92.81%	56.61%
% of Contaminated Announcements to All Announced Loans	39.88%	12.55%	7.19%	43.39%

Table 2.2: Variable Descriptions and Summary Statistics

This table presents the variable names, definitions, and summary statistics of loan deals from the Dealscan from 1994-2014. Panel A, B, and C provides the loan, borrowing firm, and lender characteristics respectively.

Panel A: Loan Characteristics

Variable	Definition	N	Mean	Std. dev.	Min	Median	Max
DSIZE_MIL	Loan deal size (in million$).	11,635	549.58	1,071.49	1	200	26,000
N_LOAN_FINCOV	Number of financial covenants.	11,635	1.34	1.29	0	1	7
REVOLVER_DEAL	Equals 1 if the deal consists of revolver loans only, and 0 otherwise.	11,635	0.72	0.45	0	1	1
TERM_LOAN_DEAL	Equals 1 if the deal consists of term loans only, and zero otherwise.	11,635	0.07	0.25	0	0	1
W_DEAL_MATURITY	Maturity of the deal, calculated as the weighted average maturity of all loans included in the deal (months).	11,635	47.54	29.68	1	48	377.14
NLENDER	Number of lenders involved in the deal.	11,635	7.77	8.21	1	5	290
D_LOAN_SECURED	Equals to 1 if the deal is secured, and 0 otherwise.	11,635	0.46	0.50	0	0	1
MCRISIS	The market crisis indicator variable. Equals to 1 if the deal active date is during the Russian debt crisis and the LTCM bailout (1998:Q3–1998:Q4), or during the dotcom bubble and the 9/11 crisis (2000:Q2–2002:Q3), and 0 otherwise. The crisis timeline follows Berger and Bouwman (2013).	11,635	0.18	0.38	0	0	1
BCRISIS	The banking crisis indicator variable. Equals to 1 if the deal active date is during the recent subprime mortgage crisis (2007:Q3–2009:Q4). The crisis timeline follows Berger and Bouwman (2013).	11,635	0.08	0.27	0	0	1

(Continued)

Table 2.2: Variable Descriptions and Summary Statistics

Panel B: Borrowing Firm Characteristics

Variable	Definition	N	Mean	Std. dev.	Min	Median	Max
NEVER_ISSUE_BOND	Equals to 1 if the borrowing firm never issue public bonds during the sample period, and 0 otherwise.	11,635	0.58	0.49	0	1	1
NR	Equals to 1 if the borrowing firm does not have a long-term or short-term issuer credit rating, and 0 otherwise.	11,635	0.51	0.50	0	1	1
INDEX_IA	The information asymmetry index, calculated as the average of the quintile ranking of a firm based on the six information asymmetry measures, following Maskara and Mullineaux (2011). Larger value shows more information asymmetry.	11,510	2.60	0.92	0.38	2.50	5
AT	The borrowing firm's total assets (in million $).	11,635	6,859.71	27,973.87	1.92	971.96	797,769
SMALL_BORROWER	Equals to 1 if the borrowing firm's total assets below the median.	11,635	0.50	0.50	0	0	1
TOBIN_Q	The borrowing firm's Tobin's Q, calculated as the ratio of the borrowing firm's book value of debt plus market value of equity to its total assets, following Billet, Flannery, and Garfinkel (1995).	11,635	1.75	1.60	0.25	1.40	77.63
LEVERAGE	The borrowing firm's market leverage, calculated as the book value of total debt divided by the sum of total debt plus the market value of equity, following Billet, Flannery, and Garfinkel (1995).	11,635	0.41	0.22	0.00	0.39	0.99
EBITDAR	The ratio of operating income before depreciation to total assets, following Billet, Flannery, and Garfinkel (1995).	11,635	0.12	0.12	-1.61	0.13	0.94

(Continued)

Table 2.2: Variable Descriptions and Summary Statistics

Panel C: Lender Characteristics

Variable	Definition	N	Mean	Std. dev.	Min	Median	Max
LENDER_AT	The lead lender's total assets (in million $).	11,635	897,893.60	785,617.40	992.29	668,641	2,415,689
BIG3_LENDER	The dominant lead lender indicator. Equals to 1 if the lead lender is one of the big three lenders in the year of deal active date, and 0 otherwise.	11,635	0.69	0.46	0	1	1
LENDER_EQTA	The lead lender's capitalization, calculated as the ratio of equity to total assets.	11,635	0.08	0.02	0.03	0.08	0.15
RL_IND	An indicator variable of relationship lending, following Bharath, Dahiya, Saunders, and Srinivasan (2011). Equals to 1 if the lead lender has a previous lending relationship with the borrowing firms in the last 5 years, and 0 otherwise.	11,635	0.31	0.46	0	0	1
RL_NUM	A measure of relationship lending intensity, following Bharath, Dahiya, Saunders, and Srinivasan (2011). Calculated as the ratio between number of loans made by the same lender to the borrowing firm in the last 5 years and total number of loans received by the borrowing firm in the last 5 year.	11,635	0.27	0.42	0	0	1

(Continued)

Table 2.2: Variable Descriptions and Summary Statistics

Panel C: Lender Characteristics

Variable	Definition	N	Mean	Std. dev.	Min	Median	Max
RL_AMT	A measure of relationship lending intensity, following Bharath, Dahiya, Saunders, and Srinivasan (2011). Calculated as the ratio between dollar amount of loans made by the same lender to the borrowing firm in the last 5 years and total dollar amount of loans received by the borrowing firm in the last 5 year.	11,635	0.27	0.43	0	0	1
NONBANK_L	Equals to 1 if the lead lender is nonbank financial institution, and 0 otherwise.	11,635	0.03	0.17	0	0	1
MS_NONBANK	The market share of nonbank lead lenders, calculated as the total dollar amount of loans made by nonbank lead lenders in a particular year divided by the total dollar amount of loans made during the year by all lead lenders.	11,635	0.02	0.02	0.00	0.02	0.10

Table 2.3: Cumulative Abnormal Stock Returns following Loan Announcements

Panel A shows the Cumulative Average Abnormal Returns (CAARs) following 8-K clean loan announcements. Panel B shows CAARs following 8-K loan announcements that are contaminated with other events. Panel C shows CAARs of unannounced loans around their active date. I use market model as the main estimation model, and Fama-French 3 Factors and 5 Factors models as robustness checks. CS-t is the Cross-Sectional test statistic, BMP-t is the Standardized Cross-Sectional test statistic as in Boehmer, Musumeci, and Poulsen (1991), and Patell-Z is the event study test statistic as in Patell (1976).

Panel A: Cumulative Abnormal Stock Returns following "Clean" Loan Announcements

				CAAR Test Statistics		
Estimation Model	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	2,161	0.456%	3.17***	2.82***	3.23***
	[-1,+1]	2,161	0.346%	2.93***	2.34**	2.68***
	[0,+2]	2,161	0.395%	3.02***	2.22**	2.61***
Market Model	[0,+1]	2,161	0.376%	3.33***	2.55**	3.11***
	[0,0]	2,161	0.071%	1.14	0.62	0.67
	[-1,0]	2,161	0.042%	0.51	0.62	0.65
	[-2,0]	2,161	0.131%	1.29	1.79*	1.92*
	[-2,+2]	2,161	0.405%	2.80***	2.47**	2.88***
	[-1,+1]	2,161	0.274%	2.31**	1.77*	2.07**
	[0,+2]	2,161	0.343%	2.66***	1.86*	2.20**
Fama-French 3 Factors Model	[0,+1]	2,161	0.325%	2.91***	2.15**	2.66***
	[0,0]	2,161	0.034%	0.55	0.01	0.01
	[-1,0]	2,161	-0.017%	-0.21	-0.09	-0.10
	[-2,0]	2,161	0.088%	0.88	1.36	1.49

(Continued)

Table 2.3: Cumulative Abnormal Stock Returns following Loan Announcements

Panel A: Cumulative Abnormal Stock Returns following "Clean" Loan Announcements

				CAAR Test Statistics		
Estimation Model	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	2,161	0.425%	2.92***	2.52**	2.99***
	[-1,+1]	2,161	0.292%	2.42**	1.86*	2.21**
	[0,+2]	2,161	0.346%	2.65***	1.80*	2.16**
Fama-French 5 Factors Model	[0,+1]	2,161	0.327%	2.88***	2.08**	2.62***
	[0,0]	2,161	0.028%	0.43	0.11	0.13
	[-1,0]	2,161	-0.007%	-0.08	-0.03	-0.03
	[-2,0]	2,161	0.097%	0.96	1.41	1.59

Panel B: Cumulative Abnormal Stock Returns following "Contaminated" Loan Announcements

				CAAR Test Statistics		
	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	1,413	0.510%	2.48**	2.39**	3.11***
	[-1,+1]	1,412	0.270%	1.60	1.56	2.13**
	[0,+2]	1,414	0.531%	3.06***	3.71***	5.08***
Market Model	[0,+1]	1,413	0.388%	2.55**	2.79***	4.06***
	[0,0]	1,413	0.077%	0.84	1.60	2.06**
	[-1,0]	1,412	-0.038%	-0.31	-0.03	-0.04
	[-2,0]	1,412	0.061%	0.42	0.15	0.19

(Continued)

Table 2.3: Cumulative Abnormal Stock Returns following Loan Announcements

Panel B: Cumulative Abnormal Stock Returns following "Contaminated" Loan Announcements

				CAAR Test Statistics		
	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
Fama-French 3 Factors Model	[-2,+2]	1,413	0.525%	2.59***	2.47**	3.25***
	[-1,+1]	1,412	0.253%	1.51	1.36	1.88*
	[0,+2]	1,414	0.530%	3.10***	3.72***	5.11***
	[0,+1]	1,413	0.380%	2.53**	2.68***	3.93***
	[0,0]	1,413	0.081%	0.89	1.64	2.14**
	[-1,0]	1,412	-0.046%	-0.37	-0.07	-0.09
	[-2,0]	1,412	0.080%	0.54	0.30	0.38
Fama-French 5 Factors Model	[-2,+2]	1,413	0.495%	2.45**	2.11**	2.83***
	[-1,+1]	1,412	0.228%	1.39	1.15	1.60
	[0,+2]	1,414	0.513%	3.02***	3.43***	4.79***
	[0,+1]	1,413	0.357%	2.41**	2.43**	3.58***
	[0,0]	1,413	0.085%	0.94	1.53	2.03**
	[-1,0]	1,412	-0.043%	-0.35	-0.13	-0.17
	[-2,0]	1,412	0.071%	0.48	0.08	0.11

(Continued)

Table 2.3: Cumulative Abnormal Stock Returns following Loan Announcements

Panel C: Cumulative Abnormal Stock Returns of “Unannounced” Loans around Deal Active Date

				CAAR Test Statistics		
	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	7,796	0.400%	2.96***	4.19***	5.69***
	[-1,+1]	7,798	0.261%	2.05**	2.95***	4.58***
	[0,+2]	7,799	0.414%	3.22***	4.49***	7.03***
Market Model	[0,+1]	7,799	0.269%	2.22**	2.8***	4.87***
	[0,0]	7,798	0.178%	1.55	1.78*	3.87***
	[-1,0]	7,798	0.170%	1.41	2.03**	3.49***
	[-2,0]	7,796	0.164%	1.34	1.76*	2.59***
	[-2,+2]	7,796	0.331%	2.46**	3.68***	5.03***
	[-1,+1]	7,798	0.207%	1.62	2.46**	3.85***
	[0,+2]	7,799	0.362%	2.81***	3.94***	6.2***
Fama-French 3 Factors Model	[0,+1]	7,799	0.236%	1.94*	2.38**	4.18***
	[0,0]	7,798	0.145%	1.26	1.37	3.01***
	[-1,0]	7,798	0.114%	0.94	1.54	2.65***
	[-2,0]	7,796	0.109%	0.90	1.35	2.01**
	[-2,+2]	7,796	0.321%	2.37**	3.56***	4.93***
	[-1,+1]	7,798	0.202%	1.59	2.48**	3.91***
	[0,+2]	7,799	0.342%	2.65***	3.74***	5.96***
Fama-French 5 Factors Model	[0,+1]	7,799	0.225%	1.84*	2.32**	4.11***
	[0,0]	7,798	0.140%	1.22	1.38	3.05***
	[-1,0]	7,798	0.117%	0.97	1.63	2.84***
	[-2,0]	7,796	0.117%	0.95	1.45	2.17**

(Continued)

Table 2.3: Cumulative Abnormal Stock Returns following Loan Announcements

Panel D: Cumulative Abnormal Stock Returns of "Unannounced" Revolver Loans around Deal Active Date

				CAAR Test Statistics		
Estimation Model	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
Market Model	[-2,+2]	5,656	0.107%	1.06	1.37	1.53
	[-1,+1]	5,657	0.041%	0.99	1.51	1.55
	[0,+2]	5,657	0.061%	1.07	1.59	1.61
	[0,+1]	5,657	0.047%	1.01	1.53	1.58
	[0,0]	5,656	0.009%	0.19	0.64	0.74
	[-1,0]	5,657	-0.029%	-0.46	-0.81	-0.90
	[-2,0]	5,656	-0.028%	-0.38	-0.35	-0.37
FF 3 Factors	[-2,+2]	5,656	0.106%	1.09	1.44	1.60
	[-1,+1]	5,657	-0.027%	-0.35	-1.10	-1.25
	[0,+2]	5,657	0.060%	1.43	1.56	1.58
	[0,+1]	5,657	0.031%	0.46	1.12	1.32
	[0,0]	5,656	-0.025%	-0.51	-0.04	-0.05
	[-1,0]	5,657	-0.083%	-1.34	-0.15	-0.17
	[-2,0]	5,656	-0.082%	-1.12	-0.12	-0.13
FF 5 Factors	[-2,+2]	5,656	0.106%	1.07	1.36	1.36
	[-1,+1]	5,657	-0.028%	-0.36	-1.15	-1.33
	[0,+2]	5,657	0.059%	1.52	1.57	1.58
	[0,+1]	5,657	0.020%	0.29	1.01	1.20
	[0,0]	5,656	0.076%	0.73	0.17	0.21
	[-1,0]	5,657	-0.082%	-1.32	-0.26	-0.29
	[-2,0]	5,656	-0.076%	-1.02	-0.01	-0.02

Table 2.4: Bank-Dependent Firms' Cumulative Abnormal Stock Returns following Loan Announcements

Panel A shows Cumulative Average Abnormal Returns (CAARs) following 8-K clean loan announcements for bank-dependent firms. I define bank-dependent firms as those that never issue public bonds during the sample period from 1994-2014. Panel B shows CAARs following 8-K clean loan announcements for non-bank-dependent firms, which also issue public bonds during the sample period. The public bonds issuance data are from the Mergent FISD. I use market model as the main estimation model, and Fama-French 3 Factors and 5 Factors models as robustness checks. CS-t is the Cross-Sectional test statistic, BMP-t is the Standardized Cross-Sectional test statistic as in Boehmer, Musumeci, and Poulsen (1991), and Patell-Z is the event study test statistic as in Patell (1976).

Panel A: Cumulative Abnormal Stock Returns following Clean Loan Announcements by Bank-Dependent Firms

				CAAR Test Statistics		
	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	1,254	0.779%	3.8***	3.66***	4.26***
	[-1,+1]	1,254	0.598%	3.49***	3.32***	3.78***
	[0,+2]	1,254	0.703%	3.63***	3.38***	4.02***
Market Model	[0,+1]	1,254	0.629%	3.75***	3.56***	4.40***
	[0,0]	1,254	0.136%	1.62	1.54	1.57
	[-1,0]	1,254	0.104%	0.96	1.35	1.34
	[-2,0]	1,254	0.206%	1.51	2.24**	2.35**
	[-2,+2]	1,254	0.735%	3.54***	3.41***	4.03***
	[-1,+1]	1,254	0.521%	3.00***	2.87***	3.36***
	[0,+2]	1,254	0.636%	3.32***	3.01***	3.57***
Fama-French 3 Factors Model	[0,+1]	1,254	0.567%	3.39***	3.17***	3.98***
	[0,0]	1,254	0.110%	1.29	1.32	1.37
	[-1,0]	1,254	0.064%	0.58	1.10	1.12
	[-2,0]	1,254	0.194%	1.42	2.15**	2.33**

(Continued)

Table 2.4: Bank-Dependent Firms' Cumulative Abnormal Stock Returns following Loan Announcements

Panel A: Cumulative Abnormal Stock Returns following Clean Loan Announcements by Bank-Dependent Firms

				CAAR Test Statistics		
	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	1,254	0.735%	3.52***	3.5***	4.18***
	[-1,+1]	1,254	0.538%	3.07***	2.98***	3.54***
	[0,+2]	1,254	0.632%	3.27***	3.01***	3.61***
Fama-French 5 Factors Model	[0,+1]	1,254	0.575%	3.41***	3.18***	4.04***
	[0,0]	1,254	0.100%	1.16	1.17	1.24
	[-1,0]	1,254	0.062%	0.54	1.14	1.19
	[-2,0]	1,254	0.180%	1.28	2.13**	2.37**

Panel B: Cumulative Abnormal Stock Returns following Clean Loan Announcements by Non-Bank-Dependent Firms

				CAAR Test Statistics		
	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	907	0.010%	0.05	0.02	0.03
	[-1,+1]	907	-0.002%	-0.01	-0.27	-0.31
	[0,+2]	907	-0.032%	-0.20	-0.60	-0.69
Market Model	[0,+1]	907	0.024%	0.18	0.32	0.38
	[0,0]	907	-0.019%	-0.20	-0.70	-0.81
	[-1,0]	907	-0.044%	-0.36	-0.52	-0.57
	[-2,0]	907	0.026%	0.18	0.18	0.20

(Continued)

Table 2.4: Bank-Dependent Firms' Cumulative Abnormal Stock Returns following Loan Announcements

Panel B: Cumulative Abnormal Stock Returns following Clean Loan Announcements by Non-Bank-Dependent Firms

				CAAR Test Statistics		
	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	907	-0.052%	-0.28	-0.26	-0.30
	[-1,+1]	907	-0.067%	-0.45	-0.64	-0.75
	[0,+2]	907	-0.061%	-0.39	-0.68	-0.80
Fama-French 3 Factors Model	[0,+1]	907	-0.009%	-0.07	-0.47	-0.57
	[0,0]	907	-0.071%	-0.78	-1.35	-1.59
	[-1,0]	907	-0.128%	-1.06	-1.32	-1.46
	[-2,0]	907	-0.058%	-0.41	-0.40	-0.45
	[-2,+2]	907	-0.003%	-0.01	-0.26	-0.30
	[-1,+1]	907	-0.049%	-0.32	-0.63	-0.75
	[0,+2]	907	-0.050%	-0.31	-0.75	-0.91
Fama-French 5 Factors Model	[0,+1]	907	-0.015%	-0.11	-0.56	-0.70
	[0,0]	907	-0.073%	-0.80	-1.37	-1.65*
	[-1,0]	907	-0.102%	-0.84	-1.20	-1.35
	[-2,0]	907	-0.016%	-0.11	-0.30	-0.34

Table 2.5: Cumulative Abnormal Stock Returns following Public Bond Announcements

This table shows Cumulative Average Abnormal Returns (CAARs) following public bond announcements from 1994-2014. I use the public bond offering date as the announcement date. The public bonds issuance data are from the Mergent FISD. I use market model as the main estimation model, and Fama-French 3 Factors and 5 Factors models as robustness checks. CS-t is the Cross-Sectional test statistic, BMP-t is the Standardized Cross-Sectional test statistic as in Boehmer, Musumeci, and Poulsen (1991), and Patell-Z is the event study test statistic as in Patell (1976).

				CAAR Test Statistics		
	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	2,934	-0.363%	-3.15***	-2.71***	-3.05***
	[-1,+1]	2,934	-0.449%	-5.08***	-4.2***	-4.86***
	[0,+2]	2,934	-0.336%	-4.14***	-2.87***	-3.15***
Market Model	[0,+1]	2,934	-0.317%	-4.57***	-3.49***	-3.94***
	[0,0]	2,934	-0.250%	-4.76***	-4.4***	-5.4***
	[-1,0]	2,934	-0.382%	-4.97***	-4.79***	-5.82***
	[-2,0]	2,934	-0.277%	-2.84***	-3.22***	-3.9***
	[-2,+2]	2,934	-0.388%	-3.42***	-3.04***	-3.46***
	[-1,+1]	2,934	-0.476%	-5.43***	-4.47***	-5.26***
	[0,+2]	2,934	-0.384%	-4.78***	-3.57***	-3.94***
Fama-French 3 Factors Model	[0,+1]	2,934	-0.348%	-5.01***	-3.96***	-4.53***
	[0,0]	2,934	-0.269%	-5.1***	-4.76***	-5.97***
	[-1,0]	2,934	-0.398%	-5.19***	-4.94***	-6.13***
	[-2,0]	2,934	-0.275%	-2.85***	-3.22***	-3.97***

(Continued)

Table 2.5: Cumulative Abnormal Stock Returns following Public Bond Announcements

				CAAR Test Statistics		
	Event Window	N	CAAR	CS-t	BMP-t	Patell-Z
	[-2,+2]	2,934	-0.403%	-3.55***	-3.24***	-3.79***
	[-1,+1]	2,934	-0.485%	-5.54***	-4.59***	-5.52***
	[0,+2]	2,934	-0.393%	-4.86***	-3.6***	-4.07***
Fama-French 5 Factors Model	[0,+1]	2,934	-0.348%	-4.95***	-3.89***	-4.54***
	[0,0]	2,934	-0.268%	-5.08***	-4.68***	-5.95***
	[-1,0]	2,934	-0.407%	-5.32***	-5.07***	-6.41***
	[-2,0]	2,934	-0.282%	-2.9***	-3.37***	-4.26***

Table 2.6: Variance Inflation Factor (VIF) of Main Independent Variables

This table shows the Variance Inflation Factors (VIFs) of main independent variables used in the multivariate analysis. The VIFs are generated using the *estat vif* command in Stata 12 following a linear probability model regression of clean loan announcement indicator variable (CLEAN_AN) on all of the main independent variables. The main independent variables include loan, borrowing firms, and lender characteristics, and two instrument variables. The instrument variables are SOX_REG that equals 1 for loans having deal active date post the Sarbanes-Oxley enactment (July 2002 onward) and 0 otherwise, and 8K_REG that equals to 1 for loans having deal active date post the effective date of the SEC Rule #33-8400 (August 2004 onward) and 0 otherwise.

Variable	VIF	1/VIF
LN_LENDER_AT	4.24	0.24
8K_REG	3.86	0.26
SOX_REG	3.52	0.28
LN_DSIZE_MIL	2.76	0.36
BIG3_LENDER	2.68	0.37
LEVERAGE	2.67	0.37
LN_TOBIN_Q	2.43	0.41
SMALL_BORROWER	2.23	0.45
LENDER_EQTA	1.83	0.55
D_LOAN_SECURED	1.52	0.66
MCRISIS	1.48	0.68
NONBANK_L	1.46	0.68
REVOLVER_DEAL	1.41	0.71
NEVER_ISSUE_BOND	1.32	0.76
LN_ MATURITY	1.30	0.77
TERM_LOAN_DEAL	1.27	0.78
MS_NONBANK	1.26	0.79
EBITDAR	1.24	0.81
N_LOAN_FINCOV	1.23	0.81
BCRISIS	1.18	0.84
RL_IND	1.05	0.95
Mean VIF	2.00	

Table 2.7: Factors Affecting Clean Loan Announcement

This table presents the regression estimates of the probability a loan to be announced by the borrowing firm. CLEAN_AN equals to 1 if a loan is cleanly announced in 8-K, and 0 otherwise. Column (1)-(5) employs probit regression models, while column (6) uses a logit regression model for a robustness check. SOX_REG equals 1 for loans having deal active date post the Sarbanes-Oxley enactment (July 2002 onward) and 0 otherwise, and 8K_REG equals to 1 for loans having deal active date post the effective date of the SEC Rule #33-8400 (August 2004 onward) and 0 otherwise. All coefficient estimates are the average marginal impacts to the probability of loan announcement. All borrowing firm and lender characteristics are lagged one fiscal year. Standard errors are clustered at the borrowing firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Numbers in parentheses are t-statistics.

	Dependent Variable: CLEAN_AN					
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
SOX_REG	0.056***	0.066***	0.070***	0.060***	0.050***	0.066***
	(4.111)	(4.596)	(4.876)	(4.219)	(3.281)	(3.661)
8K_REG	0.232***	0.235***	0.243***	0.238***	0.222***	0.229***
	(19.142)	(19.000)	(19.721)	(19.350)	(15.651)	(14.562)
MCRISIS		0.033**	0.036***	0.036***	0.031**	0.040**
		(2.466)	(2.688)	(2.724)	(2.259)	(2.440)
BCRISIS		0.010	0.005	0.010	0.014	0.013
		(0.903)	(0.498)	(0.962)	(1.290)	(1.253)
BORROWING FIRM CHARACTERISTICS:						
NEVER_ISSUE_BOND			0.012	0.010	0.010	0.012
			(1.339)	(1.054)	(1.068)	(1.295)
SMALL_BORROWER			0.026***	0.007	0.008	0.006
			(2.858)	(0.603)	(0.692)	(0.514)
LN_TOBIN_Q			-0.015	-0.007	-0.006	-0.007
			(-1.284)	(-0.617)	(-0.488)	(-0.595)
LEVERAGE			0.037	0.037	0.034	0.022
			(1.410)	(1.422)	(1.298)	(0.837)
EBITDAR			-0.034	-0.049	-0.056*	-0.058*
			(-1.156)	(-1.599)	(-1.770)	(-1.711)
LOAN CHARACTERISTICS:						
LN_DSIZE_MIL				-0.001	-0.002	-0.003
				(-0.219)	(-0.531)	(-0.694)
N_LOAN_FINCOV				0.022***	0.023***	0.022***
				(7.255)	(7.459)	(7.098)
REVOLVER_DEAL				0.026***	0.027***	0.031***
				(2.775)	(2.913)	(3.226)
TERM_LOAN_DEAL				-0.002	-0.002	-0.002
				(-0.160)	(-0.132)	(-0.119)
LN_ MATURITY				0.028***	0.026***	0.026***
				(4.338)	(3.972)	(3.729)

(Continued)

Table 2.7: Factors Affecting Clean Loan Announcement

	Dependent Variable: CLEAN_AN					
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
D_LOAN_SECURED				0.022**	0.022**	0.020**
				(2.434)	(2.478)	(2.234)
LENDER CHARACTERISTICS:						
RL_IND					0.015**	0.016**
					(2.018)	(2.166)
LENDER_EQTA					0.514*	0.473*
					(1.936)	(1.773)
LN_LENDER_AT					0.009*	0.009
					(1.807)	(1.613)
BIG3_LENDER					-0.002	-0.002
					(-0.119)	(-0.153)
MS_NONBANK					0.034	0.030
					(0.164)	(0.129)
NONBANK_LENDER					0.066***	0.060**
					(2.606)	(2.254)
Observations	11,635	11,635	11,635	11,635	11,635	11,635
Pseudo-R^2	0.154	0.154	0.158	0.170	0.172	0.170
Number of clusters	3730	3730	3730	3730	3730	3730

Table 2.8: Factors Affecting Contaminated Loan Announcement

This table presents the regression estimates of the probability a loan to be announced by the borrowing firm together with other events. CONT_AN equals to 1 if a loan is announced in 8-K together with other events, and 0 otherwise. Column (1)-(5) employs probit regression models, while column (6) uses a logit regression model for a robustness check. SOX_REG equals 1 for loans having deal active date post the Sarbanes-Oxley enactment (July 2002 onward) and 0 otherwise, and 8K_REG equals to 1 for loans having deal active date post the effective date of the SEC Rule #33-8400 (August 2004 onward) and 0 otherwise. All coefficient estimates are the average marginal impacts to the probability of loan announcement. All borrowing firm and lender characteristics are lagged one fiscal year. Standard errors are clustered at the borrowing firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Numbers in parentheses are t-statistics.

	Dependent Variable: CONT_AN					
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
SOX_REG	0.001	-0.001	0.005	-0.001	-0.020	-0.025
	(0.059)	(-0.023)	(0.221)	(-0.053)	(-0.859)	(-0.677)
REG_8K	0.295***	0.296***	0.299***	0.298***	0.283***	0.348***
	(15.463)	(15.392)	(15.624)	(15.113)	(14.057)	(11.439)
MCRISIS		-0.007	-0.003	-0.002	-0.011	-0.016
		(-0.332)	(-0.152)	(-0.102)	(-0.490)	(-0.450)
BCRISIS		-0.013*	-0.014*	-0.007	0.004	0.006
		(-1.691)	(-1.890)	(-0.875)	(0.481)	(0.771)
BORROWING FIRM CHARACTERISTICS:						
NEVER_ISSUE_BOND			-0.003	-0.005	-0.006	-0.007
			(-0.375)	(-0.673)	(-0.860)	(-0.936)
SMALL_BORROWER			0.024***	0.019**	0.020**	0.018*
			(3.270)	(2.119)	(2.207)	(1.947)
LN_TOBIN_Q			0.005	0.010	0.011	0.013
			(0.524)	(1.001)	(1.089)	(1.190)
LEVERAGE			0.012	0.014	0.012	0.010
			(0.528)	(0.613)	(0.507)	(0.402)
EBITDAR			0.027	0.001	0.001	-0.002
			(0.872)	(0.028)	(0.034)	(-0.066)
LOAN CHARACTERISTICS:						
LN_DSIZE_MIL				0.001	0.002	0.002
				(0.405)	(0.562)	(0.586)
N_LOAN_FINCOV				0.019***	0.021***	0.021***
				(7.543)	(8.098)	(8.113)
REVOLVER_DEAL				-0.029***	-0.026***	-0.026***
				(-3.770)	(-3.425)	(-3.450)
TERM_LOAN_DEAL				-0.050***	-0.048***	-0.050***
				(-3.936)	(-3.746)	(-3.841)

(Continued)

Table 2.8: Factors Affecting Contaminated Loan Announcement

	Dependent Variable: CONT_AN					
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
LN_ MATURITY				0.023***	0.022***	0.024***
				(3.849)	(3.578)	(3.712)
D_LOAN_SECURED				-0.008	-0.010	-0.012
				(-1.022)	(-1.319)	(-1.566)
LENDER CHARACTERISTICS:						
RL_IND					-0.014**	-0.015**
					(-2.218)	(-2.377)
LENDER_EQTA					0.992***	1.011***
					(4.519)	(4.524)
LN_LENDER_AT					0.004	0.005
					(0.813)	(0.954)
BIG3_LENDER					0.006	0.002
					(0.468)	(0.201)
MS_NONBANK					-0.506	-0.697**
					(-1.537)	(-2.032)
NONBANK_LENDER					0.062***	0.066***
					(2.913)	(2.937)
Observations	11,635	11,635	11,635	11,635	11,635	11,635
Pseudo-R^2	0.242	0.243	0.244	0.259	0.263	0.264
Number of clusters	3730	3730	3730	3730	3730	3730

Table 2.9: Factors Affecting CAR following Clean Loan Announcement

This table presents the regression estimates of Cumulative Abnormal Returns (CARs) following clean loan announcements on a variety of determinants, including market and banking crisis, as well as borrowing firm, loan, and lender characteristics. The dependent variable in column (1)-(4) is CAR[0,+1], and CAR[0,+2] in column (5)-(7). Regression coefficients in column (1) are estimated using OLS without correcting for the sample selection bias. The rest of the columns are estimated using the Heckman selection model, which are based on Heckman (1979) using a maximum-likelihood procedure (Maddala, 1983). Ross (2010) advocates this procedure to address the heteroscedasticity in abnormal returns. As further robustness checks, I compare the results of CARs following loan announcements using three different estimation models: market model, Fama-French 3 factors, and Fama-French 5 factors model. RUNUP is the cumulative abnormal returns using each of the estimation models over the interval [-12,-3], a proxy for the stock price runup pre a loan announcement. All columns control for Industry and Year Fixed Effects. All borrowing firm and lender characteristics are lagged one fiscal year. Standard errors are clustered at the borrowing firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Numbers in parentheses are t-statistics.

	OLS	Heckman Models					
		Dependent Variable: CAR[0,+1]			Dependent Variable: CAR[0,+2]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variable	Market Model	Market Model	FF 3 Factors	FF 5 Factors	Market Model	FF 3 Factors	FF 5 Factors
RUNUP	0.018	0.007	-0.000	0.005	0.037	0.028	0.031
	(0.694)	(0.353)	(-0.025)	(0.288)	(1.608)	(1.296)	(1.214)
MCRISIS	-0.009	-0.016	-0.015	-0.019	-0.018	-0.019	-0.024
	(-0.645)	(-1.158)	(-1.111)	(-1.255)	(-1.095)	(-1.148)	(-1.300)
BCRISIS	0.013**	0.016***	0.017***	0.015***	0.015**	0.014**	0.012*
	(2.532)	(2.893)	(3.039)	(2.662)	(2.351)	(2.328)	(1.942)
INVERSE MILLS (λ)		0.071***	0.072***	0.073***	0.075***	0.076***	0.077***
		(6.41)	(6.38)	(6.42)	(7.17)	(7.42)	(7.64)

(Continued)

Table 2.9: Factors Affecting CAR following Clean Loan Announcement

	OLS	Heckman Models					
		Dependent Variable: CAR[0,+1]			Dependent Variable: CAR[0,+2]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variable	Market Model	Market Model	FF 3 Factors	FF 5 Factors	Market Model	FF 3 Factors	FF 5 Factors
BORROWING FIRM CHARACTERISTICS:							
NEVER_ISSUE_BOND	0.008***	0.009***	0.008**	0.009***	0.009**	0.009**	0.009**
	(2.851)	(2.588)	(2.529)	(2.640)	(2.391)	(2.398)	(2.458)
SMALL_BORROWER	0.001	0.002	0.002	0.002	0.004	0.003	0.003
	(0.206)	(0.425)	(0.452)	(0.393)	(0.816)	(0.695)	(0.616)
LN_TOBIN_Q	0.004	-0.001	-0.001	-0.001	-0.001	-0.000	-0.000
	(0.971)	(-0.291)	(-0.241)	(-0.171)	(-0.222)	(-0.085)	(-0.056)
LEVERAGE	0.014	0.006	0.007	0.009	0.007	0.007	0.010
	(1.274)	(0.553)	(0.631)	(0.741)	(0.517)	(0.534)	(0.723)
EBITDAR	-0.022	-0.027	-0.019	-0.020	-0.041**	-0.035*	-0.031
	(-1.360)	(-1.597)	(-1.154)	(-1.189)	(-2.056)	(-1.702)	(-1.511)
LOAN CHARACTERISTICS:							
LN_DSIZE_MIL	0.000	0.001	0.001	0.001	0.002	0.002	0.002
	(0.351)	(0.710)	(0.781)	(0.740)	(0.955)	(1.047)	(1.089)
N_LOAN_FINCOV	-0.001	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(-0.988)	(3.328)	(3.445)	(3.626)	(2.936)	(3.080)	(3.366)
REVOLVER_DEAL	0.001	0.008**	0.007*	0.007*	0.007	0.007*	0.008*
	(0.342)	(1.972)	(1.788)	(1.812)	(1.629)	(1.663)	(1.825)
TERM_LOAN_DEAL	0.012	0.007	0.008	0.007	0.003	0.005	0.003
	(1.320)	(0.896)	(1.096)	(0.908)	(0.368)	(0.611)	(0.377)
LN_MATURITY	-0.000	0.006*	0.006*	0.006*	0.005	0.006*	0.005
	(-0.167)	(1.825)	(1.921)	(1.774)	(1.604)	(1.752)	(1.544)

(Continued)

Table 2.9: Factors Affecting CAR following Clean Loan Announcement

	OLS	Heckman Models					
		Dependent Variable: CAR[0,+1]			Dependent Variable: CAR[0,+2]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variable	Market Model	Market Model	FF 3 Factors	FF 5 Factors	Market Model	FF 3 Factors	FF 5 Factors
D_LOAN_SECURED	-0.001	0.005	0.004	0.005	0.004	0.004	0.004
	(-0.522)	(1.472)	(1.286)	(1.450)	(1.006)	(1.067)	(1.226)
LENDER CHARACTERISTICS:							
RL_IND	0.002	0.005*	0.005*	0.004	0.003	0.003	0.002
	(0.762)	(1.682)	(1.714)	(1.549)	(0.944)	(0.955)	(0.794)
LENDER_EQTA	-0.145	-0.037	-0.038	-0.023	-0.139	-0.122	-0.107
	(-1.439)	(-0.323)	(-0.345)	(-0.205)	(-1.051)	(-0.923)	(-0.807)
LN_LENDER_AT	0.000	0.003	0.001	0.002	0.001	0.000	0.001
	(0.155)	(0.949)	(0.517)	(0.714)	(0.361)	(0.087)	(0.198)
BIG3_LENDER	-0.004	-0.004	-0.002	-0.002	-0.002	-0.000	-0.000
	(-0.750)	(-0.677)	(-0.377)	(-0.384)	(-0.234)	(-0.070)	(-0.006)
MS_NONBANK	1.894	-7.563***	-8.151***	-8.140***	-10.880***	-10.680***	-10.607***
	(1.220)	(-3.458)	(-3.619)	(-3.627)	(-4.271)	(-4.111)	(-4.089)
NONBANK_LENDER	-0.000	0.013	0.013	0.012	0.004	0.004	0.005
	(-0.009)	(1.085)	(1.032)	(0.962)	(0.278)	(0.282)	(0.337)
Constant	0.035	-0.117**	-0.102**	-0.111**	-0.079	-0.075	-0.083
	(0.833)	(-2.255)	(-2.033)	(-2.116)	(-1.334)	(-1.280)	(-1.370)
Industry FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	2,172	11,635	11,635	11,635	11,635	11,635	11,635
R-squared	0.037	0.008	0.006	0.005	0.020	0.016	0.016
Number of clusters	1345	3730	3730	3730	3730	3730	3730

Table 2.10: Additional Robustness Checks—BHAR and Raw Return

This table presents the regression estimates of Buy-and-Hold Abnormal Return (BHAR) and Cumulative Raw Return (CRET) following Loan Announcements on a variety of determinants, including market and banking crisis, as well as borrowing firm, loan, and lender characteristics. The dependent variable in column (1)-(3) is BHAR[0,+2], and CRET[0,+2] in column (4). All regression coefficients are estimated using the Heckman selection model, which are based on Heckman (1979) using a maximum-likelihood procedure (Maddala, 1983). Ross (2010) advocates this procedure to address the heteroscedasticity in abnormal returns. For the BHAR regressions, three different estimation models are used: market model, Fama-French 3 factors, and Fama-French 5 factors model. RUNUP is the cumulative abnormal returns using each of the estimation models over the interval [-12,-3], a proxy for the stock price runup pre a loan announcement. All columns control for Industry and Year Fixed Effects. All borrowing firm and lender characteristics are lagged one fiscal year. Standard errors are clustered at the borrowing firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Numbers in parentheses are t-statistics.

	Dependent Variable:			
	BHAR[0,+2]			CRET[0,+2]
	(1)	(2)	(3)	(4)
Independent Variable	Market Model	FF 3 Factors	FF 5 Factors	Raw Return
RUNUP	0.041*	0.031	0.033	0.036
	(1.908)	(1.530)	(1.495)	(1.513)
MCRISIS	-0.018	-0.019	-0.023	-0.033**
	(-1.090)	(-1.158)	(-1.289)	(-1.965)
BCRISIS	0.015**	0.014**	0.012**	0.012*
	(2.407)	(2.356)	(1.962)	(1.877)
INVERSE MILLS (λ)	0.077***	0.078***	0.079***	0.083***
	(8.93)	(9.15)	(9.29)	(9.12)
BORROWING FIRM CHARACTERISTICS:				
NEVER_ISSUE_BOND	0.009**	0.009**	0.009**	0.009**
	(2.378)	(2.397)	(2.466)	(2.128)
SMALL_BORROWER	0.004	0.004	0.003	0.006
	(0.889)	(0.765)	(0.688)	(1.146)
LN_TOBIN_Q	-0.001	-0.001	-0.001	-0.003
	(-0.271)	(-0.126)	(-0.108)	(-0.465)
LEVERAGE	0.007	0.008	0.010	0.003
	(0.560)	(0.574)	(0.749)	(0.224)
EBITDAR	-0.039**	-0.033	-0.029	-0.034*
	(-2.005)	(-1.635)	(-1.445)	(-1.697)

(Continued)

Table 2.10: Additional Robustness Checks—BHAR and Raw Return

	Dependent Variable:			
	BHAR[0,+2]			CRET[0,+2]
Independent Variable	(1) Market Model	(2) FF 3 Factors	(3) FF 5 Factors	(4) Raw Return
LOAN CHARACTERISTICS:				
LN_DSIZE_MIL	0.002	0.002	0.002	0.002
	(1.021)	(1.116)	(1.167)	(0.852)
N_LOAN_FINCOV	0.005***	0.005***	0.006***	0.005***
	(3.108)	(3.253)	(3.536)	(2.987)
REVOLVER_DEAL	0.007*	0.007*	0.008*	0.007
	(1.714)	(1.749)	(1.917)	(1.452)
TERM_LOAN_DEAL	0.002	0.004	0.002	0.000
	(0.224)	(0.497)	(0.270)	(0.045)
LN_MATURITY	0.006*	0.006*	0.005*	0.007**
	(1.755)	(1.903)	(1.667)	(1.989)
D_LOAN_SECURED	0.004	0.004	0.005	0.005
	(1.065)	(1.113)	(1.270)	(1.353)
LENDER CHARACTERISTICS:				
RL_IND	0.003	0.003	0.002	0.002
	(0.925)	(0.937)	(0.766)	(0.748)
LENDER_EQTA	-0.133	-0.115	-0.100	-0.127
	(-1.020)	(-0.882)	(-0.762)	(-0.893)
LN_LENDER_AT	0.001	0.001	0.001	0.001
	(0.463)	(0.177)	(0.277)	(0.220)
BIG3_LENDER	-0.002	-0.001	-0.000	0.000
	(-0.284)	(-0.125)	(-0.058)	(0.018)
MS_NONBANK	-11.086***	-10.899***	-10.819***	-14.134***
	(-4.699)	(-4.517)	(-4.473)	(-5.792)
NONBANK_LENDER	0.004	0.004	0.005	0.004
	(0.299)	(0.303)	(0.358)	(0.302)
Constant	-0.088	-0.084	-0.091	-0.091
	(-1.552)	(-1.484)	(-1.560)	(-1.537)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	11,635	11,635	11,635	11,635
R-squared	0.017	0.012	0.011	0.017
Number of clusters	3730	3730	3730	3730

CHAPTER 3

DEPOSIT INSURANCE COVERAGE, OWNERSHIP, AND RISK TAKING: EVIDENCE FROM A NATURAL EXPERIMENT[20,21]

3.1 INTRODUCTION

As one primary component of financial safety nets, deposit insurance (DI) aims to protect small depositors, promote public confidence, and enhance banking system stability (BCBS and IADI, 2009). This objective aligns with Diamond and Dybvig (1983)'s study that theorizes the risk of self-fulfilling or information-driven bank runs can be mitigated by providing an insurance scheme to depositors that guarantees their deposits money (full or partially) in case of bank defaults. Believing that DI can achieve this objective, the number of countries around the world that implement DI explicitly has been growing substantially.[22] During the recent 2008 financial crisis, many of these countries relied on their DIs (along with other bailouts and liquidity provision) to restore public confidence and prevent systemic bank runs. In particular, there were 19 countries

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[22] The International Association of Deposit Insurers (IADI) records that as of August 2016, there are 123 countries have established explicit DISs and 34 countries are considering to implement it. Back in 1974, there were only 12 countries that had explicit DISs.

provided full depositors guarantee, 22 countries increased their DI statutory coverage limit (hereafter will be shortly referred as "coverage") permanently, and 7 countries increased their DI coverage limit temporarily (IADI and IMF, 2010). Anginer, Demirguc-Kunt, and Zhu (2014) show that these countries' decisions were reasonable as the study finds that countries with DI tend to have lower bank risk and more systemic stability during the crisis.

Despite of its increasing popularity, a large strand of previous literature shows that DI may induce a moral hazard problem. The problem arises since DI acts like a put option that limits banks' downside risk and reduces incentives for depositors to discipline their banks (e.g. Merton, 1977; Marcus and Shaked, 1984; Duan, Moreau, and Sealey, 1992; Allen and Saunders, 1993). Hence, DI creates incentives for banks to expropriate the government or tax payers by taking excessive risk (e.g. Bhattacharya and Thakor, 1993; Barth, Caprio, and Levine, 2004). The moral hazard problem reduces the effectiveness of DI and harms banking system stability.[23] Therefore, whether DI can really benefit the banking system stability remains an open empirical question.

Moreover, whether banks will take advantage on the DI generosity in terms of risk taking might be affected by their ownership structure. First, there is a principal-agent problem between bank managers and shareholders. On the one hand, bank shareholders aim to maximize their shares value and therefore prefer higher risk-taking. Bank managers, on the other hand, might concern more on their job security and therefore tend to be more risk averse. Some empirical studies show that higher stock holdings by bank

[23] For example in 1980, shortly before the U.S. Saving and Loans crisis, the FDIC had increased its coverage limit from $40,000 to $100,000 per depositor per bank or approximately nine times per capita GDP. This generous coverage policy together with financial liberalization and regulatory failure are believed as the main triggers of the Saving and Loans crisis (Kane, 1992). Kane analogues the generous deposit insurance as feeding off the "zombie" S&Ls using taxpayers' money.

managers can alleviate this principal-agent problem (Saunders, Strock, and Travlos, 1990; Berger and Imbierowich, 2014). Second, there is a large strand of literatures in corporate finance showing that not all of firms' shareholders aim to maximize the market value of equity. For example, the owners of a family firm may have a longer investment time horizon and concern more on their heirs' control to the firm (Anderson and Reeb, 2003). This means that the basic assumption of the Merton's model (1977) for DI may not be relevant for banks with different ownership structure. Surprisingly, the empirical studies that relate different kind of ownership structure and bank-risk taking are still relatively sparse.

In terms of empirical research design, the causality between DI coverage and bank risk taking is challenging to test because there is a potential reverse causality problem between these two variables. On the one hand, an increase in DI coverage could induce more bank risk taking as it provides banks with more protection from downside risk, as well as erodes incentives for depositors to monitor their banks' risk (*the moral hazard hypothesis*). On the other hand, in a harsh time when bank risk is high such as the recent 2008 financial crisis, the government may react to increase DI coverage to enhance depositors' confidence to the banking system, which results in lower bank risk and greater systemic stability (*the safety net hypothesis*). Therefore, in a regression of bank risk taking on DI coverage, it is important to find an exogenous source of variation in DI coverage that is not affected by bank risk. Otherwise, the regression estimates will be biased.

In this paper, I examine how DI coverage affects bank risk taking and how different kinds of bank ownership structures influence this relation using a natural experiment of exogenous variation in DI coverage in the Indonesian commercial banking industry over 2002Q1-2011Q4.[24] During this period, Indonesia has experienced several changes in DI coverage, both decrease and increase. Indonesia also has not imposed any coinsurance requirement and still relies on the flat rate pricing (non-risk-sensitive premium) for the DI service provided during this period.[25] Therefore, Indonesia provides a unique empirical setting that can address the reverse causality problem between DI coverage and bank risk taking. In addition, focusing on a panel of banks within a single country will be able to mitigate heterogeneity bias that complicates most of empirical studies using cross-countries data.

Since January 1998, the Government of Indonesia (GOI) had provided a blanket guarantee (BG) program that insured all bank liabilities (deposits and nondeposit funding, including off balance sheet activities such as derivatives) in order to restore public confidence and tame the impact of the 1997/1998 Asian financial crisis (Enoch, Baldwin, Frecaut, and Kovanen, 2001). In September 2004, the GOI enacted *Law Number 24 Year 2004* to establish an explicit DI program by the Indonesia Deposit Insurance Corporation (IDIC). The law mandated to end the BG regime and start a limited DI program gradually. In the law, the GOI explicitly states that a full guarantee (FG) program will be in place of the BG from September 2005 until March 2006. Different than BG, FG did not insure bank liabilities other than deposits, but insured bank deposits fully. After March 2006, the law explicitly mandates a limit to DI coverage that will gradually decrease from IDR 5 billion (until September 2006), 1 billion (until March 2007), and

[24] Islamic commercial banks are excluded from the analysis since they have substantial differences in business characteristics which are based on non-usury economics.
[25] The DI coverage, coinsurance requirement, and risk-based premium pricing are primary tools for DI to curb banks' moral hazard problem (Mccoy, 2008).

100 million respectively.[26] Since these gradual decreases in DI coverage were stated explicitly in the law, all Indonesian banks became effectively aware of this policy since the law was enacted in September 2004. More importantly, the decreases in DI coverage were predetermined in the law and therefore they are not affected by bank risk taking during the implementation period of the law.

The other exogenous variation in DI coverage starts from October 2008, when the GOI decided to increase DI coverage, following similar policy by the US government and neighboring countries around the subprime mortgage crisis period. Despite that none of Indonesian banks has direct exposure to subprime mortgage, the GOI decided to increase the DI coverage from IDR 100 million to 2 billion in October 2008. The GOI reasoned that they took the policy along with a bailout decision of *PT Bank Century* on November 2008 in order to prevent the subprime crisis to precipitate into the Indonesian economy by eroding market and public confidence psychologically (The Indonesia Ministry of Finance, 2010). Since the crisis was originated from the subprime mortgage problem in the US while Indonesian banks had no direct exposures on the subprime mortgage instruments, the increase in DI coverage was exogenous.

By way of preview, I find a significant positive relation between explicit deposit insurance coverage and bank risk-taking, consistent with the moral hazard hypothesis. More specifically, controlling for various bank-specific and macroeconomic variables, as well as bank regulations, I find that Indonesian banks' Z-score, an inverse measure of bank risk taking, increases on average about 18% when the government switched from the blanket guarantee era to the limited guarantee era administered by the Indonesian Deposit Insurance Corporation (IDIC). In terms of mechanisms in which explicit DI

[26] IDR stands for Indonesian Rupiah, the official local currency of Indonesia.

coverage influences bank risk taking, I find that a lower explicit DI coverage is associated with lower standard deviation of profitability and higher capitalization, though it is also associated with lower bank profitability. Furthermore, I find some evidence that the relation is non-monotonic at the low level of explicit DI coverage, in line with the safety net hypothesis. This finding suggests that there is an optimum range of explicit DI coverage. Finally, I find significant evidence that the impact of explicit DI coverage on bank risk is different across different kinds of ultimate owners. In particular, family banks and politically connected banks are those that are most affected when the government switched from the blanket guarantee era to the limited guarantee era, suggesting that the moral hazard problem in these banks are more prominent compared to foreign banks and nonpolitically connected banks.

This paper contributes to the literature in several areas. First, this paper complements existing literature on deposit insurance and bank risk-taking in developing countries. Next, this paper provides unique empirical settings that isolate the impact of deposit insurance coverage changes on bank risk-taking. Finally, this paper extends the existing literature by examining the degree of bank risk-taking for different types of bank ownership.

The remainder of this paper is organized as follows. Section 3.2 provides some institutional backgrounds on the Indonesia banking industry. Section 3.3 reviews the previous literature and hypothesis development. Section 3.4 describes the data and methodology. Section 3.5 presents the main empirical finding and robustness checks. Section 3.6 concludes.

3.2 INSTITUTIONAL BACKGROUND

In response to the 1997/1998 financial crisis, the Indonesian government provided a blanket guarantee (BG) for its domestic banks in order to restore public confidence toward Indonesian banking system and mitigate bank runs.[27] The BG guaranteed all commercial banks' liabilities, excluding loan capital, subordinated debt, illegal liabilities, liabilities to the banks' related parties, and derivative transactions.[28] The BG program was funded from the government fiscal budget and from the fixed-rate premium paid by each participating bank for 0.25% of deposits per year. However, the BG was not applicable to branch offices of foreign banks and none of joint venture banks were willing to join the BG program. Therefore, none of the branch office of foreign banks and joint-venture bank was insured by the BG program.

In September 2004, the Indonesian government enacted Law Number 24 Year 2004 to establish the Indonesia Deposit Insurance Corporation (IDIC) which officially began its operation on September 2005. According to the Law, the membership of the IDIC's deposit insurance program is compulsory for all banks in Indonesia, including branch office of foreign banks and joint-venture banks. The Law mandates the end of the BG program and gradually decreases the deposit insurance coverage within 18 months from its effective enforcement date as follows:

a. Period 9/22/2005 to 3/21/2006: Full Guarantee (FG)
b. Period 3/22/2006 to 9/21/2006: IDR 5 billion (USD 500,000)
c. Period 9/22/2006 to 3/21/2007: IDR 1 billion (USD 100,000)

[27] The BG program was officially administered by an institution called the Indonesian Bank Restructuring Agency (IBRA).
[28] The BG also guaranteed for off-balance sheet items and currency swap transactions. For further details see Kusumaningtuti (1998).

d. Period 3/22/2007 and after: IDR 100 million (USD 10,000)

As the main source of funding, the IDIC charges a fixed-rate premium amounting 0.20% of deposits per year.

In response to the recent 2008 global financial crisis, the Indonesian government enacted the Government Regulation Number 66 Year 2008 to increase the deposit maximum coverage from IDR 100 million (USD 10,000) to IDR 2 billion (USD 200,000). Different than other countries that increase their deposit insurance coverage temporarily (e.g. Australia, Brazil, Netherlands, New Zealand, Switzerland, Ukraine, and United States[29]), the Indonesian government does not specify an exit strategy for this pre-emptive policy when the crisis is over. Though the increase of deposit insurance coverage was considered as one of the Indonesian government's public policies which has successfully restored the Indonesian banking stability during the crisis (Basri and Raharja, 2010), the amount of optimal deposit insurance coverage which minimizes Indonesian banks' risk-taking still remains unanswered.

3.3 LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

3.3.1 DEPOSIT INSURANCE COVERAGE AND BANK RISK-TAKING

A large body of literature in deposit insurance contends that a generous explicit deposit insurance coverage may induce bank instability due to higher moral hazard problem (**the Moral Hazard hypothesis**). Early interest in the deposit insurance was initiated by the seminal article by Merton (1977), who viewed the deposit insurance as a put option issued by the government on the banks' assets. From the viewpoint of banks

[29] In response to the 2008 global financial crisis, the U.S. government had increased their deposit insurance cap temporarily from USD100,000 to USD250,000. However, by the Dodd-Frank law in July 2010, the temporary increase was made permanent.

holding the put option, there is an incentive to increase the value of the option by surging the volatility of banks' assets and shift the losses incurred to the government or taxpayers, creating a moral hazard problem. Kane (1992) shows how a generous deposit insurance coverage may become one of primary triggers of the 1980s U.S. Savings and Loans (S&Ls) crisis. Kane blames the deposit insurance for breaking the link between what the S&Ls' assets could earn and what depositors could expect to be repaid. Cebula and Belton (1997) study the impact of federal deposit insurance coverage on the failure rate of commercial banks in the U.S. during the 1963-1991 periods and find that the higher extent of explicit deposit insurance coverage is associated with higher bank failure rate. Based on cross-section data from 61 countries in 1980-1997, Demirgüç-Kunt and Detragiache (2002) find that explicit deposit insurance tends to have adverse impact on bank stability and the impact is stronger as the coverage level becomes more extensive and where it is run by the government instead of the private sector. Cull, Senbet, and Sorge (2005) examine the relation between the explicit deposit insurance generosities and financial development using the data from 37 countries between 1960 and 2001. They show that generous government-funded deposit insurance has an adverse impact on financial development and growth in the long run, except in countries whose strong rule of laws and bank supervisors. By utilizing contingency table analysis to 52 countries over the period 1996-2007, Chu (2011) finds that low deposit insurance coverage beats both high and full coverage in sustaining bank stability due to better market discipline and lower moral hazard problem. Using the U.S. and 21 countries data during the pre-crisis period in 1997-2007 and the crisis and post-crisis period in 2008-2010, Berger and Turk-Ariss (2013) find that depositors' discipline decline during and after the crisis as a result of the government actions to expand the deposit insurance coverage and rescue troubled financial institutions. Still in line with the findings of the mainstream literature, Lambert, Noth, and Schüwer (2013) provide within-country evidence from the U.S. data around the introduction of the *Emergency Stabilization Act* in Q4 2008, that an increase in the amount of insured deposits triggers higher investments in risky loans, suggesting riskier behavior on affected banks. Therefore, according to the Moral Hazard Hypothesis, the first hypothesis to test in this paper is:

HYPOTHESIS 1: All else equal, lower deposit insurance coverage is associated with lower bank-risk taking.

On the flip side of literature, there is **a Safety-Net Hypothesis**, which contends that a low deposit insurance coverage is associated with higher bank-risk taking, and hence, lower bank stability. Dreyfus, Saunders, and Allen (1994) develop a theoretical model to examine the optimal caps on the scope of insured deposits given the deposit insurer adopts a flat-rate premium system.[30] They posit that uninsured depositors tend to require higher interest rate or risk premium to their banks if the deposit insurance coverage level is too low. This may make some banks unable to retain their depositors or reduce their profit margin, and therefore, it will either increase the banks' likelihood of being insolvent or induce the banks to conduct riskier assets substitution. Based on the data of 128 banks in EU during 1991-1998, Gropp and Vesala (2004) find some evidences that high explicit deposit insurance coverage is associated with lower banks' risk-taking and that implicit guarantee of banks' creditors is relatively high when there is

[30] Theory suggests that a flat deposit insurance premium rate does not provide incentive to reduce the moral hazard problem caused by excessive bank risk taking (De Long and Saunders, 2011). Hence, we may expect that under a flat premium rate regime, banks' risk-taking will change when the government alters the deposit insurance coverage.

low explicit protection. Meanwhile, Anginer, Demirgüç-Kunt, and Zhu (2012) examine the data from 96 countries during 2004-2009 and find that the stabilization effect tends to dominate the moral hazard effect of deposit insurance during a financial crisis, though the overall effect over the full sample remains negative. Therefore, according to the Safety-Net Hypothesis, the first hypothesis to test in this paper is:

HYPOTHESIS 2: All else equal, lower deposit insurance coverage is associated with higher bank-risk taking.

More recent literature in deposit insurance suggests a non-monotonic relationship between deposit insurance coverage and bank stability, as pioneered by Angkinand and Wihlborg (2006; 2010). Their model assumes that every country having explicit deposit insurance also provides implicit guarantee. The reason why every country tends to provide implicit guarantee is that during banking crises, the pressures to the government to bail out troubled banks or to provide blanket guarantees are very intense (Demirgüç-Kunt, Kane, and Laeven, 2008). Angkinand and Wihlborg propose that the degree of implicit guarantee will depend on the level of explicit deposit insurance coverage. When the explicit coverage is low, uninsured depositors and creditors tend to have stronger expectation that the government will respond banking crises by issuing blanket guarantees or bailing out distressed banks and hence, it may lead to higher bank risk-taking or lower bank stability due to higher implicit protection. On the contrary, when the explicit deposit insurance coverage is high, the credibility of non-insurance increases as well. However, as the mainstream literature noted, higher explicit deposit insurance coverage is generally associated with higher risk-taking or lower bank stability. Therefore, the total effects of explicit deposit insurance coverage on bank risk-taking might follow a U-shaped curve. With respect to this strands of literature, our third hypothesis to test in this paper is:

HYPOTHESIS 3: All else equal, there is a non-monotonic relation between bank-risk taking and the level of explicit deposit insurance coverage.

3.3.2 OWNERSHIP STRUCTURE

Strands of literature suggest that corporate governance has important consequences to bank stability.[31] Among the most recent literatures, Laeven and Levine (2009) examine the relation between bank governance, regulation, and risk taking using the data of 10 largest publicly listed banks from 48 countries. Consistent with the previous literature (e.g. Jensen and Meckling, 1976; John, Litov, and Yeung, 2008), they find that banks having large owners with substantial cash flow (CF) rights exhibit higher risk taking behavior. They argue that by focusing on the large shareholders' CF rights, instead of voting rights, they capture directly both the incentives of owners toward risk and the ability of owners to influence banks' risk. Further, they find that given banks having large equity owner, the presence of explicit deposit insurance is associated with higher risk taking.

Regarding the effect of managerial ownership on risk-taking behavior, several studies have shown the importance of managerial ownership in determining bank stability. For example Saunders, Strock, and Travlos (1990), Gorton and Rosen (1995), Anderson and Fraser (2000), and Sullivan and Spong (2007) find that higher shareholdings of officers and directors induces a higher bank risk-taking behavior due to

[31] We suggest to see Berger, Imbierowicz, and Rauch (2013) for a comprehensive literature review on the influences of corporate governance to bank stability.

lesser degree of agency problem between banks' managers and shareholders. More specific, Berger, Imbierowicz, and Rauch (2013) find that high shareholding by lower-level management (e.g. vice presidents) is associated with significant increase in default risk. However, they do not find direct impact of the shareholdings by outside directors and chief officers on banks' probability of failure.

Other aspects of corporate governance may impact on bank stability are foreign, government, and family ownership, as well as listing status. The presence of foreign ownership in the banks tend to be associated with better performance (e.g. Claessens, Demirgüç-Kunt, and Huizinga, 2001) and less risk taking (e.g. Laeven, 1999), especially in developing countries. Foreign banks are also supervised both by the home and host regulators. Next, listed banks are expected to be more transparent and have greater market monitoring (Hadad, Agusman, Monroe, Gasbarro, and Zumwalt, 2011). Therefore, we may expect that foreign banks and listed banks have better governance and hence become more stable than domestic banks and unlisted banks. Concerning government ownership, most of the existing literature finds negative influence on bank stability. Using the sample of European commercial banks, Iannotta, Nocera, and Sironi (2007) find that government- owned banks tend to have poorer loan quality and higher insolvency risk than other type of banks. Still using the sample of European banks, Iannotta, Nocera, and Sironi (2013) find further that government-owned banks have lower credit risk but higher operating risk, indicating the presence of governmental protection that induces risk taking, and also find that the government-owned banks may serve certain political goals. However, Hossain, Jain, and Mitra (2013) find that partial state ownership of banks, specifically in the Asia-Pacific regions, helps avoid sharp losses during financial crises by restricting risky-business activities. Meanwhile, the impact of family ownership on banks' risk taking may vary. For example, Morck, Yavuz, and Yeung (2011) find that banking systems which are thoroughly controlled by tycoons or families have less efficient capital allocation, slower economic growth, and greater financial instability which may imply greater risk taking by the banks in such banking systems. The higher risk may result from higher incentives to expropriate non-family shareholders via tunneling or lack pools of talents (e.g. Morck, Stangeland, and Yeung, 2000; Bloom and Van Reenen, 2006). On the other hand, there are strands of literature find that family firms are more conservative, have superior monitoring abilities compared to widely-held firms, have longer investment horizons, and hence tends to be more stable (e.g. Demsetz and Lehn, 1985; James, 1999; Anderson and Reeb, 2003; Barry, Lepetit, and Tarazi, 2011). Furthermore, Angkinand and Wihlborg (2010) assert that banks' quality of governance may affect the relation between explicit deposit insurance coverage and banks' risk-taking. In particular, the U-shaped curvature becomes more pronounced when the quality of banks' governance is more aligned with shareholders' wealth maximization objective (good governance).

Therefore, the next hypotheses to test in this paper are:

HYPOTHESIS 4A: Banks having more alignment of interest with shareholder maximization objective have higher sensitivity of risk to deposit insurance coverage changes.

HYPOTHESIS 4B: Banks having less alignment of interest with shareholder maximization objective have lower sensitivity of risk to deposit insurance coverage changes.

3.4 DATA AND VARIABLES

3.4.1 THE SAMPLE

We test the impact of deposit insurance coverage and ownership structure on the Indonesian bank risk-taking using bank-level data from Indonesian commercial banking industry. The sample starts from Q1:2002, the earliest data available publicly from the bank regulator's website, until Q4:2011.[32] I end the sample in 2011:Q4 as the regulator implements the IFRS accounting for all banks starting from 2012:Q1 onward.[33] In our sample, we exclude all Islamic banks from the analysis since they have substantial differences in business characteristics from conventional banks. We obtain all the financial information from the quarterly financial reports which are mandatorily submitted by all commercial banks in Indonesia to the bank regulator. All financial information is inflation-adjusted using the GDP deflator index with the year 2000 as its base year. Meanwhile, the ownership database is constructed from the annual-bank management and ownership structure reports which are also available in the bank regulator's website. We complement the ownership database with the information from the banks' websites, magazines, and other information sources, in case if there is less complete information about a bank's ownership structure on its annual report. The macroeconomic indicators including real GDP growth, GDP deflator index, and deposit insurance rate are gathered from the Indonesian Economic and Financial Statistics (SEKI) published by the Bank of Indonesia and the Indonesian Central Statistical Bureau (BPS).

[32] These data are available online via Bank of Indonesia's website, http://www.bi.go.id, the former bank regulator, or from the Indonesian Financial Service Authority (Otoritas Jasa Keuangan)'s website http://www.ojk.go.id, the new bank regulator starting on 2013 onward.

[33] Bank of Indonesia's Circulation Letter No. 11/4/DPNP.

I conduct standard filtering procedure by excluding all commercial banks with negative, zero and missing gross-total assets and loan composition since these data are likely subject to errors, leaving 3,971 bank-quarter observations in the final sample.[34] In order to mitigate the impact of outliers on our analysis, income statement and balance sheet-related variables are winsorized at the top and bottom 1% of the distribution, unless mentioned otherwise.

3.4.2 BANK-RISK TAKING MEASURE

Following Berger, Klapper, and Turk-Ariss (2009), we use the Z-score (*ZSCORE*) as the main inverse measure of bank-risk taking. The time-varying Z-score is calculated using the following formula (on Boyd, De Nicoló, and Jalal, 2006):

$$Z_i = \frac{\mu_{ROA_i} + \mu_{EQTA_i}}{\sigma_{ROA_i}} \qquad (1)$$

where μ_{ROA_i}, μ_{EQTA_i}, and σ_{ROA_i} are the four quarters period-average return on gross-total assets, -average equity to gross-total assets, and –standard deviation of return on gross-total assets. Using the common definition of z-score, a bank is defined as insolvent when its $\left(EQTA_i + ROA_i\right) \le 0$. This means that at this state, the bank does not have enough capital to absorb its losses. Hannan and Hanweck (1988) and Boyd, Graham, and Hewitt (1993) show that if *ROA* is a random variable with mean μ_{roa} and finite variance σ^2_{roa}, then the upper bound of the probability of insolvency is as follows:

$$p(ROA_i \le -EQTA_i) \le Z^{-2} \qquad (2)$$

[34] Following Berger and Bouwman (2013), we use gross total assets (GTA) instead of total assets, which equals to total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve. The purpose of the reversal is to measure the full value of the loans financed. Helwege (1996) suggests similar measure of gross assets instead of net assets for the S&Ls.

As the *Z-SCORE* commonly has a highly skewed distribution, I follow Laeven and Levine (2009) to use the natural logarithm of the *Z-SCORE* instead (*LN ZSCORE*). To avoid truncation of data observations due to negative *ZSCORE*s, I use the following log transformation:

$$LNZSCORE = \ln(1 + |\min(ZSCORE)| + ZSCORE \tag{3}$$

Lower *ZSCORE* and *LNZSCORE* implies higher bank-risk taking.

3.4.3 EXPLICIT DEPOSIT INSURANCE COVERAGE

To measure the different regime of deposit insurance coverage, I use six different indicator variables that capture the transition era (*DCOV_TR*), the full deposits guarantee era (*DCOV_FG*), the IDR 5 billion deposit insurance coverage era (*DCOV_5B*), the IDR 1 billion deposit insurance coverage era (*DCOV_1B*), the IDR 100 million deposit insurance coverage era (DCOV_100M), and the IDR 2 billion deposit insurance coverage era (*DCOV_2B*). The base indicator variable that is omitted in the main regressions is the blanket guarantee era (DCOV_BG), so that the regression estimates of the other indicator variables of deposit insurance coverage regimes are interpreted relative to this base category.

3.4.4 OWNERSHIP

We use several proxies to measure different type of bank ownership. First, we use the percentage of the manager's cash flow rights (*MANCF*), i.e. the cash flow right of bank manager if the manager is one of the ultimate owners. Ultimate owners are defined as the top owners in the bank's ownership structure that have at least 10% voting rights, following Laeven and Levine (2009) and Carney and Child (2013). Next, we measure the largest ultimate owner's cash flow right (*UCASH*) and the wedge between cash flow right and voting right of the largest ultimate owner (*WEDGE*).

For different type of ownerships, we use indicator variables for foreign, family, government, and private-politically connected banks. A foreign bank is defined as a bank that has foreign institutions as the largest ultimate owners. By this definition, all branches of foreign banks are defined as foreign banks, including joint-venture banks which satisfy this definition. A bank is defined as a family bank if the largest ultimate shareholder is a family or a family-based business group. There are two kinds of state-owned banks in Indonesia: central-government owned banks (*Bank Persero*) and regional-government owned banks (*Bank Pembangunan Daerah*). This separation follows the banks' classification by the Bank of Indonesia. Also, after the enactment of Law Number 22 and Number 25 Year 1999 concerning the local government decentralization, we may expect that the dependency of local government's budget to the local-government owned banks' incomes are higher. A central-government owned bank is defined as a bank that has the central government as the largest ultimate owner. Similarly, a local-government owned bank is defined as a bank that has the regional government as the largest ultimate owner. Finally, a private-politically connected bank is defined as a private bank with at least one of the commissioners, directors, or controlling shareholders is a current of former political party member, parliament member, or government official, following Nys, Tarazi, and Trinugroho (2015).[35]

[35] Different than the organizational structure in most of the U.S. firms, Indonesia embraces a two-tier system, where the executives (led by a CEO) conduct the operational business activities and the Board of Commissioner (led by a President Commissioner) is responsible to monitor the executives on behalf of the firm's shareholders.

3.4.5 CONTROL VARIABLES

We use various control variables consist of bank-level and macroeconomic-level variables. For the bank-level variables, I use the log natural of gross-total assets (*LNGTA*) and its square term (*LNGTA_SQ*) to account for economies of scale in managing risk (Enkhbold and Otgonshar, 2013), the assets composition (the ratio of loans to gross-total assets, *LOANGTA*, and the ratio of fixed assets to gross-total assets, *FAGTA*). We also control for the role of nondeposit funding as theory suggests that nondeposit funding and subordinated debts' investors may impose more market discipline on banks compared to depositors, and hence, increase the banks' stability (e.g. Berger and Turk-Ariss, 2013). To do so, we use the ratio of Nondeposits funding-to-GTA ratio (NDEPGTA) as a proxy.

Following Berger, Klapper, and Turk-Ariss (2009), we use the Lerner index as a proxy for market power. The Lerner Index measures the mark-up of price over marginal costs, as shown by the following formula.

$$Lerner_{it} = (P_{GTA_{i,t}} - MC_{GTA_{i,t}}) / P_{GTA_{i,t}} \tag{4}$$

where $P_{GTA_{i,t}}$ is the price of gross-total assets proxied by the ratio of total interest and non-interest income to gross-total assets for bank *i* at time *t*, and $MC_{GTA_{i,t}}$ is the marginal cost of gross-total assets for bank *i* at time *t*. The $MC_{GTA_{i,t}}$ is estimated using the following translog cost function:

$$\ln Cost_{it} = \beta_0 + \beta_1 \ln Q_{it} + \frac{\beta_2}{2} \ln Q_{it}^2 + \sum_{k=1}^{3} \gamma_{kt} \ln W_{k,it} + \sum_{k=1}^{3} \phi_k \ln Q_{it} \ln W_{k,it}$$

$$+ \sum_{k=1}^{3} \sum_{j=1}^{3} \ln W_{k,it} \ln W_{j,it} + \varepsilon_{it} \tag{5}$$

where Q_{it} represents a proxy for bank output, i.e. the gross-total assets of bank *i* at time *t*, and $W_{k,it}$ are three input prices of labor (the ratio of personnel expenses to gross-total assets), funds (the ratio of interest expenses to total deposits), and fixed capital (the ratio of other operating and administrative expenses to gross total assets). Year fixed effects are also added in the estimation process of the equation (5) above with robust standard errors. I winsorize $W_{1,2,3}$ at 3% level on top and bottom instead of 1% level as the latter still leave considerable numbers of outliers. Next, the $MC_{GTA_{i,t}}$ is calculated using the formula below:

$$MC_{GTA_{it}} = \frac{Cost_{it}}{Q_{it}}\left[\beta_1 + \beta_2 \ln Q_{it} + \sum_{k=1}^{3}\phi_k \ln W_{k,it}\right] \tag{6}$$

Finally, for the macroeconomic variables, we control for the real GDP growth (*EGROWTH*), crisis dummy (CRISIS), and the deposit insurance rate (*DI_RATE*).[36] The details of all variables used in this paper, their definition, and summary statistics are shown in Table 3.1.

3.5 EMPIRICAL RESULTS

3.5.1 CORRELATION STRUCTURE BETWEEN INDEPENDENT VARIABLES

Table 3.2 presents the pairwise correlation coefficients among independent variables used in this paper. As shown by the correlation coefficients on the table, there are no pairs of independent variables which have strong linear correlations with the

[36] The CRISIS is a dummy variable equals to 1 during the 2008 global financial crisis and 0 otherwise. Following Berger and Bouwman (2013), we define the 2008 global financial crisis period during the period of 2007:Q3 until 2009:Q4. The deposit insurance rate is the ceiling rate of deposits' interest rate which is set by the Indonesia Deposit Insurance Corporation (IDIC) every quarter and is evaluated on monthly basis. Any deposits receive interest rate above this rate is not guaranteed by the IDIC. Hence, we may expect that higher deposit insurance rate is associated with lower bank stability (lower *Z-SCORE*, higher *NPLLOAN*, or higher *stdnplcap*).

absolute value above 0.70. This means that our independent variables may not suffer from serious multicollinearity problems. (Gujarati, 2004).

3.5.2 DEPOSIT INSURANCE COVERAGE AND BANK RISK-TAKING

Table 3.3 presents the OLS regression results of deposit insurance coverage on bank-risk taking. We can see from the table that *DCOV_TR* is not statistically significant, which suggests that there is no change in bank-risk taking in the transition period compared to the blanket guarantee era. *DCOV_FG* and *DCOV_5B* are statistically significant on several specifications, but they become not statistically significant as we control more variables. This suggests that controlling all set of control variables, there are still no change in bank-risk taking during the full deposit guarantee and the IDR 5 billion deposit insurance coverage era that attributable to the reduction in deposit insurance coverage. *DCOV_1B* is statistically significant at 99% confidence level in all regression specifications, with the coefficient magnitude about 0.209. This means that compared to the blanket guarantee era, on average banks have about 23% higher *ZSCORE* during the IDR 1 billion deposit insurance coverage era.[37] *DCOV_100M* is statistically significant at 99% confidence level in all regression specifications, with the coefficient magnitude about 0.196. This means that compared to the blanket guarantee era, on average banks have about 22% higher *ZSCORE* during the IDR 100 million deposit insurance coverage era. *DCOV_2B* is also statistically significant at 99% confidence level in most of the regression specification and at 95% when we control for macroeconomic conditions and bank regulation. The coefficient estimate is about 0.131, which means that compared to

[37] Halvorsen and Palmquist (1980) show that the coefficient of a dummy variable (β_j) in a semilogarithmic regression equation should be interpreted as the $100(\exp\{\beta_j\} - 1)$ percentage change in Y for a discrete change in the dummy from 0 to 1.

the blanket guarantee era, on average banks have about 14% higher *ZSCORE* during the IDR 2 billion deposit insurance coverage era. Compared to *DCOV_1B* and *DCOV_100M*, the coefficient estimate on *DCOV_2B* is lower, which is consistent with the moral hazard hypothesis.

3.5.3 ROBUSTNESS CHECKS

Table 3.4 presents a variety of robustness checks on our main results. Panel A shows that our main results from Table 4 are robust to the exclusion of Too-Big-To-Fail banks, two-way cluster standard errors, using bank random effects instead of bank fixed effects, and controlling for time trend and its squared term.[38] Interestingly, when we exclude central-government owned and regional-government owned banks, *DCOV_2B* becomes not statistically significant. This suggests that controlling for bank-specific and macroeconomic variables, as well as bank regulation, private banks' *ZSCOREs* during the IDR 2 billion deposit insurance coverage era are not statistically different than the blanket guarantee era. In other words, there is some evidence of material increase in bank-risk taking by private banks when the government increases the deposit insurance coverage from IDR 100 million to IDR 2 billion.

Column (1) of Panel B shows the regression results if we use the IDR 5 billion deposit insurance coverage era as the base instead of the blanket guarantee era. The results show that *DCOV_1B*, *DCOV_100M*, and *DCOV_2B* are still positive and statistically significant, which suggest that compared to the IDR 5 billion deposit insurance coverage era, *ZSCORE*s in these eras with lower deposit insurance coverage are higher. This finding is still consistent with the moral hazard hypothesis. We are aware

[38] Too-Big-To-Fail (TBTF) banks defined as 15 largest banks by GTA.

of a concern that the deposit insurance coverage indicators capture some variations in bank regulation. To address this concern, we run regressions on a subsample period when there are no material changes in bank regulation (2006:Q1-2010:Q4), based on the World Bank surveys on bank regulation (Barth, Caprio, and Levine, 2013). The results are shown in column (2) of Panel B, and they are still consistent with our main findings. Next, we run placebo regressions by forwarding all deposit insurance coverage era time period by 3 years, as shown in column (3), and backwarding all deposit insurance coverage era time period by 3 years, as shown in column (4). The results show that none of the deposit insurance coverage era indicators are statistically significant, which confirms further the internal validity of our deposit insurance coverage measures.

Panel C shows the robustness check results by substituting *LNZSCORE* with alternative measures of bank-risk taking. We use three different measures of bank-risk, i.e. Standard Deviation of ROE (*SDROE*), Nonperforming Loans ratio (*NPL/TL*), and Nonperforming Assets ratio (*NPA/GTA*). The higher values of these ratios indicate higher bank risk. As we can see from the table, compared to the blanket guarantee era, we observe significant evidence that *SDROE*, *NPL/TL*, and *NPA/GTA* are lower during the limited deposit insurance coverage eras.

Finally, Panel D shows the robustness check results by expanding the transition period era to become 2003:Q1-2005:Q2.[39] I choose 2003:Q1 as the beginning of the extended transition period as the earliest news I find from Factiva about the phasing out of deposit insurance coverage up to IDR 100 million dated at January 30, 2003. As *LN ZSCORE* and *SD ROE* are calculated over 4 quarters, these measures start in 2002:Q4 and therefore, cannot be used in this extended transition regression setting. Therefore, we

[39] The formal transition era according to the Law No. 24/2004 is from 2004:Q3 - 2005:Q2.

use NPL/TL and NPA/GTA as the bank risk measures. This setting aims to address the concern that banks might anticipate the phasing out of deposit insurance coverage enacted in Law No. 24/2004. If this concern is valid, we would observe changes in bank-risk taking over this extended transition period, compared to the blanket guarantee era. Our results show that none of the *DCOV_TR_E* is statistically significant, suggesting that the concern on early anticipation by banks does not confound our main findings.

3.5.4 CHANNELS IN WHICH COVERAGE AFFECTS BANK RISK-TAKING

Table 3.5 presents the regression results of deposit insurance coverage indicators on *LNZSCORE*'s components. The table shows that compared to the blanket guarantee era, bank profitability (*MU ROA*) is lower. However, this impact is countered by the increase in bank capitalization (*MU EQ/GTA*) and decrease in standard deviation of profitability (*SD ROA*).

3.5.5 OPTIMAL RANGE OF DEPOSIT INSURANCE COVERAGE

Table 3.6 presents the regression estimates of *LN ZSCORE*, *SD ROE*, *NPL/Tl*, and *NPA/GTA* on deposit insurance coverage indicator variables, controlling for bank-specific, macroeconomic, and bank regulation variables, using the IDR 1 billion coverage period (*DCOV_1B*) as the base. This strategy enables us to estimate the coefficient of deposit insurance coverage that is lower or higher than the base's coverage. The results show that compared to the IDR 1 billion coverage period, deposit insurance coverage at IDR 5 billion or more generous are associated with lower LNZSCORE, higher SDROE, higher NPL/TL, and higher NPA/GTA. This is in line with the moral hazard hypothesis.

Meanwhile, at the IDR 2 billion coverage era, none of the *LNZSCORE, SD ROE, NPL/TL*, or *NPA/GTA* is statistically different than the IDR 1 billion coverage era. However, at the IDR 100 million coverage era, NPA/GTA becomes statistically higher than at the IDR 1 billion coverage era. This finding aligns with the safety net hypothesis. Therefore, the results show some evidence that the relation between deposit insurance coverage and bank-risk taking might be non-monotonic, suggesting that there is an optimum range of explicit deposit insurance coverage that sufficiently protects the depositors while curbing the banks' moral hazard problem (e.g. Angkinand and Wihlborg, 2010). In the case of Indonesia, this range might occur between IDR 1 billion – 2 billion.

3.5.6 OWNERSHIP STRUCTURE, COVERAGE, AND BANK RISK-TAKING

Table 3.7 presents the regression results of *LN ZSCORE* on deposit insurance coverage indicators and ownership variables for different type of ultimate shareholders, controlling for bank-specific, macroeconomic, and bank regulation variables. In general, Panel A and B show some evidence that the impact of explicit deposit insurance coverage on bank risk is different across different kinds of ultimate owners. In particular, family banks and politically connected banks are those that are most affected when the government switched from the blanket guarantee era to the limited guarantee era, suggesting that the moral hazard problem in these banks are more prominent compared to foreign banks and nonpolitically connected banks.

3.6 CONCLUSION

This paper examines the impact of deposit insurance coverage on bank risk taking and how ownership structure affects this relation. Using a natural experiment of deposit insurance coverage changes in Indonesia from 2002:Q1-2011:Q4, I find a significant positive relation between explicit Deposit Insurance coverage and bank risk-taking, consistent with the moral hazard hypothesis. More specifically, controlling for various bank-specific and macroeconomic variables, as well as bank regulations, I find that Indonesian banks' *Z-SCORE*, an inverse measure of bank risk taking, increases on average about 18% when the government switched from the blanket guarantee era to the limited guarantee era. The reduction in bank risk taking is mainly due to lower standard deviation of profitability and higher capitalization.

Next, I find some evidence that the relation is non-monotonic at the low level of explicit DI coverage, in line with the safety net hypothesis. This finding suggests that there is an optimum range of explicit DI coverage that sufficiently protects the depositors while curbing the banks' moral hazard problem. Finally, I find significant evidence that the impact of explicit deposit insurance coverage on bank risk is different across different kinds of ultimate owners. In particular, family banks and politically connected banks are those that are most affected when the government switched from the blanket guarantee era to the limited guarantee era, suggesting that the moral hazard problem in these banks are more prominent compared to foreign banks and nonpolitically connected banks.

Table 3.1: Summary Statistics

This table presents the variable names, definitions, and summary statistics of all variables used in this paper. The sample covers all Indonesian commercial banks from 2002:Q1-2011:Q4. All financial ratios are winsorized at 1% level at the top and bottom, unless specified differently. All level financial variables are denominated in billions of Indonesian Rupiah (IDR), deflated using the year 2000 implicit GDP price deflator.

Variable	Definition	N	Mean	St. Dev	P25	P50	P75
Main Bank Risk Measure:							
LN ZSCORE	A log inverse measure of bank *Z-score*. Calculated as *Ln (1+abs(minZscore)+Zscore)*.	3971	3.575	0.617	3.114	3.472	3.933
ZSCORE	An inverse measure of overall bank risk, calculated as $\frac{\mu(ROA)+\mu(EQ/GTA)}{\sigma(ROA)}$, where mean ($\mu$) and standard deviation (σ) are calculated over 4 quarters from time $t-3$ to time t. Gross Total Assets (*GTA*) are defined as bank total assets plus allowance for loans losses, following Berger and Bouwman (2013).	3971	31.635	47.759	8.921	18.610	37.456
Components of the Main Bank Risk Measure:							
MU ROA(%)	Mean of Return on Assets (Net Income/GTA), calculated from time $t-3$ to time t.	3971	1.733	1.557	0.822	1.626	2.664
SD ROA(%)	Standard deviation of ROA, calculated from time $t-3$ to time t.	3971	1.119	1.071	0.383	0.760	1.466
MU EQ/GTA(%)	Mean of Equity/GTA, calculated from time time $t-3$ to time t.	3971	13.591	8.860	8.187	10.872	16.565
Alternative Bank Risk Measures							
SD ROE (%)	Standard deviation of Return on Equity (Net Income/Total Equity), calculated over 4 quarters from time $t-3$ to time t.	3971	11.629	14.924	2.916	6.230	13.673
NPL/TL (%)	Nonperforming Loans/Total Loans	4445	4.169	5.152	1.271	2.651	4.691
NPA/GTA (%)	Nonperforming Assets/GTA	4445	2.455	2.996	0.684	1.513	2.902

(Continued)

Table 3.1: Summary Statistics

Variable	Definition	N	Mean	St. Dev	P25	P50	P75
Deposit Insurance Coverage:							
DCOV_TR	An indicator variable equals to 1 from 2004:Q3 - 2005:Q2, and 0 otherwise. This variable is an indicator of the transition period from the blanket guarantee era to the limited guarantee era, which started from the enactment date of an explicit deposit insurance (Law Number 24 Year 2004) until the effective date.	3971	0.122	0.327	0	0	0
DCOV_FG	An indicator variable equals to 1 from 2005:Q3 - 2005:Q4, and 0 otherwise. This variable is an indicator of the full deposits guarantee period, when the government terminated the guarantee on bank liabilities other than deposits and off-balance sheet items. In this period, all deposits were still guaranteed by the government through the Indonesian Deposit Insurance Corporation (IDIC).	3971	0.059	0.236	0	0	0
DCOV_5B	An indicator variable equals to 1 from 2006:Q1 – 2006:Q2, and 0 otherwise. This variable is an indicator of the period when the government started to set a nominal maximum limit on deposit guarantee (an explicit deposit insurance coverage), which was IDR 5 billion.	3971	0.062	0.242	0	0	0
DCOV_1B	An indicator variable equals to 1 from 2006:Q3 - 2006:Q4, and 0 otherwise. This variable is an indicator of the next phase out period when the government reduced the explicit deposit insurance coverage from IDR 5 billion to IDR 1 billion.	3971	0.052	0.223	0	0	0
DCOV_100M	An indicator variable equals to 1 from 2007:Q1 - 2008:Q3, and 0 otherwise. This variable is an indicator of the final phase out period, when the government reduced the explicit deposit insurance coverage from IDR 1 billion to IDR 100 million.	3971	0.193	0.395	0	0	0
DCOV_2B	An indicator variable equals to 1 from 2008:Q4 - 2011:Q4, and 0 otherwise. This variable is an indicator of the period when the government increases the explicit deposit insurance coverage from IDR 100 million to IDR 2 billion, following many other countries' responses to the recent global financial crisis.	3971	0.316	0.465	0	0	1

(Continued)

Table 3.1: Summary Statistics

Variable	Definition	N	Mean	St. Dev	P25	P50	P75
Bank Ownership Structure:							
MANCF (%)	The cash flow right of bank manager if the manager is one of the ultimate owners. Ultimate owners are defined as the top owners in the bank's ownership structure that have at least 10% voting rights, following Laeven and Levine (2009).	3927	6.210	19.185	0	0	0
UCASH (%)	The largest ultimate owner's cash flow right.	3927	72.255	28.240	48.53	80	99.8
WEDGE (%)	The wedge between cash flow right and voting right of the largest ultimate owner.	3927	0.447	2.822	0	0	0
Bank Ownership Types:							
UFAMILY	An indicator variable equals to 1 if the largest ultimate shareholder is a family or a family-based business group, and 0 otherwise.	3927	0.315	0.464	0	0	1
UFOREIGN	An indicator variable equals to 1 if the largest ultimate shareholder is a foreign institution, and 0 otherwise.	3927	0.326	0.469	0	0	1
POLCON	An indicator variable equals to 1 if the bank is a private politically connected bank, and 0 otherwise. I follow Nys, Tarazi, and Trinugroho (2015) to define a politically connected bank as a bank with at least one of the commissioners, directors, or controlling shareholders is a current of former political party member, parliament member, or government official.	3927	0.280	0.449	0	0	1
CSOB	An indicator variable equals to 1 if the bank is ultimately owned by the central (national) government, and 0 otherwise.	3927	0.036	0.187	0	0	0
RSOB	An indicator variable equals to 1 if the bank is ultimately owned by the regional (province) government, and 0 otherwise.	3927	0.199	0.399	0	0	0

(Continued)

Table 3.1: Summary Statistics

Variable	Definition	N	Mean	St. Dev	P25	P50	P75
Bank Nonfinancial Controls:							
LISTED	An indicator variable equals to 1 if a bank is publicly listed in a stock exchange, or is owned by a Bank Holding Company that is publicly listed in a stock exchange, and 0 otherwise.	3971	0.374	0.484	0	0	1
BHC	An indicator variable equals to 1 if a bank is a part of a Bank Holding Company, and 0 otherwise.	3971	0.077	0.266	0	0	0
BIGAUD	An indicator variable equals to 1 if a bank's auditor is one of the big four accounting firms, and 0 otherwise. The big four accounting firms are Ernst and Young (EY), Pricewaterhouse Coopers (PwC), KPMG, and Deloitte.	3971	0.154	0.361	0	0	0
Bank Financial Controls:							
OHRGTA (%)	Overhead ratio/GTA.	3971	4.801	4.972	3.080	4.269	5.718
NDEPGTA (%)	Nondeposits funding/GTA.	3971	1.389	3.317	0.000	0.000	1.089
IDIV (%)	Income diversification ratio, calculated as $1-\left\lvert\frac{\text{Net Interest Income-Other Operating Income}}{\text{Total Operating Income}}\right\rvert$, following Laeven and Levine (2007)	3971	18.653	24.053	1.845	7.466	27.509
FAGTA (%)	Fixed assets/GTA	3971	3.484	3.375	1.518	2.562	4.116
LOANGTA (%)	Total Loans/GTA	3971	51.710	18.566	39.533	53.757	66.650
LRGTA (%)	Log natural of real Gross Total Assets	3971	7.279	1.802	5.948	7.173	8.536
RGTA (bil. IDR)	Real Gross Total Assets, calculated as bank total assets plus allowance for loans losses, following Berger and Bouwman (2013).	3971	7,713	21,549	383	1,304	5,093

(Continued)

Table 3.1: Summary Statistics

Variable	Definition	N	Mean	St. Dev	P25	P50	P75
Bank Competition Control:							
LERNER	Lerner Index, a measure of bank market power, calculated as $(P_{GTA} - MC_{GTA})/P_{GTA}$, where P_{GTA} is the price of *GTA* proxied by the ratio of total revenues to *GTA*, and MC_{GTA} is the marginal cost of *GTA* measured as the first derivative of the following translog cost function (Berger, Klapper, and Turk-Ariss, 2009): $lnCost_{it} = \beta_0 + \beta_1 lnQ_{it} + \frac{\beta_2}{2} lnQ_{it}^2 + \sum_{k=1}^{3} \gamma_{kt} lnW_{k,it} + \sum_{k=1}^{3} \phi_k lnQ_{it} lnW_{k,it} + \sum_{k=1}^{3}\sum_{j=1}^{3} lnW_{k,it} lnW_{j,it} + \varepsilon_{it}$ where Q_{it} is bank output proxied by GTA, W_1 is the input price of labor (the ratio of personnel expense to GTA), W_2 is the input price of fund (the ratio of interest expense to total deposits), W_3 is the input price of fixed capital (the ratio of other operating and administrative expenses to total assets), and ε is the error term. I winsorize $W_{1,2,3}$ at 3% level on top and bottom instead of 1% level as the latter still leave considerable numbers of outliers.	3971	0.542	0.149	0.471	0.551	0.627
Macroeconomic Controls:							
EGROWTH (%)	Quarterly GDP growth	3971	5.394	0.909	4.560	5.551	6.055
DIRATE (%)	Deposit insurance rate	3971	9.735	3.052	7.187	8.538	11.667
Bank Regulation Controls:							
LN NBREG	Log natural of new bank regulations	3971	1.468	0.735	0.693	1.386	2.079
NBREG	Number of new bank regulations	3971	4.507	3.549	1	3	7
CRBREG	Equals to 1 on 2011:Q1 onward, and 0 otherwise. This is an indicator variable of the period when the government enacts a new package of monetary and bank regulations post the global financial crisis. This new regulation package is the largest since the 1998 Asian financial crisis.	3971	0.101	0.302	0	0	0

Table 3.2: Correlation between Independent Variables

This table presents the pairwise correlation between independent variables in each group of variable used in this paper as the right-hand side variables. The sample covers all Indonesian commercial banks from 2002:Q1-2011:Q4. All financial ratios are winsorized at 1% level at the top and bottom, unless specified differently. All level financial variables are denominated in billions of Indonesian Rupiah (IDR), deflated using the year 2000 implicit GDP price deflator.

Panel A: Deposit Insurance Coverage Indicators

	DCOV_TR	*DCOV_FG*	*DCOV_5B*	*DCOV_1B*	*DCOV_100M*	*DCOV_2B*
DCOV_TR	1					
DCOV_FG	-0.094***	1				
DCOV_5B	-0.096***	-0.065***	1			
DCOV_1B	-0.088***	-0.059***	-0.061***	1		
DCOV_100M	-0.182***	-0.123***	-0.126***	-0.115***	1	
DCOV_2B	-0.253***	-0.171***	-0.175***	-0.160***	-0.332***	1

Panel B: Bank Nonfinancial and Financial Characteristics

	LISTED	*BHC*	*BIGAUD*	*OHRGTA*	*NDEPGTA*	*IDIV*	*FAGTA*	*LOANGTA*	*LRGTA*	*LERNER*
LISTED	1									
BHC	0.357***	1								
BIGAUD	0.421***	0.112***	1							
OHRGTA	-0.078***	0.003	-0.047***	1						
NDEPGTA	0.105***	-0.021	0.110***	-0.051***	1					
IDIV	0.325***	0.325***	0.181***	-0.064***	0.060***	1				
FAGTA	-0.158***	-0.133***	-0.056***	0.278***	-0.117***	-0.241***	1			
LOANGTA	-0.061***	-0.160***	-0.037**	0.059***	0.030*	-0.128***	0.007	1		
LRGTA	0.526***	0.299***	0.470***	-0.135***	0.236***	0.358***	-0.432***	-0.047***	1	
LERNER	-0.188***	0.005	-0.102***	-0.370***	-0.053***	0.055***	-0.224***	-0.006	-0.036**	1

(Continued)

Table 3.2: Correlation between Independent Variables

Panel C: Macroeconomic and Bank Regulation Variables

	EGROWTH	*DIRATE*	*LN NBREG*	*CRBREG*
EGROWTH	1			
DIRATE	-0.424***	1		
LN NBREG	0.165***	-0.440***	1	
CRBREG	0.308***	-0.301***	-0.198***	1

Panel D. Bank Ownership Structure Variables

	MANCF	*UCASH*	*WEDGE*
MANCF	1		
UCASH	-0.138***	1	
WEDGE	0.006	-0.158***	1

Table 3.3: Deposit Insurance Coverage and Bank Risk-Taking

This table presents the OLS regression estimates of *LN ZSCORE* on deposit insurance coverage indicator variables, controlling for bank-specific, macroeconomic, and bank regulation variables. Columns (1) to (7) differ in the control variables included. All columns control for bank fixed effects except for column (1). The sample covers all Indonesian commercial banks from 2002:Q1-2011:Q4. All financial ratios are winsorized at 1% level at the top and bottom, unless specified differently. All level financial variables are denominated in billions of Indonesian Rupiah (IDR), deflated using the year 2000 implicit GDP price deflator. All control variables are lagged at time $t-4$. Standard errors are clustered at the bank level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Numbers in parentheses are t-statistics.

Independent variables:	Dependent variable: *LN ZSCORE*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DCOV_TR	0.038	0.035	0.033	0.032	0.015	0.010	0.023
	(1.071)	(0.978)	(0.894)	(0.891)	(0.410)	(0.200)	(0.462)
DCOV_FG	0.077*	0.071	0.069	0.079*	0.059	-0.023	0.022
	(1.684)	(1.544)	(1.433)	(1.682)	(1.225)	(-0.380)	(0.381)
DCOV_5B	0.094**	0.095**	0.090**	0.099**	0.083*	-0.005	0.036
	(2.175)	(2.192)	(1.999)	(2.186)	(1.772)	(-0.083)	(0.613)
DCOV_1B	0.268***	0.252***	0.250***	0.265***	0.248***	0.192***	0.209***
	(5.123)	(4.961)	(4.782)	(5.047)	(4.772)	(3.234)	(3.484)
DCOV_100M	0.272***	0.262***	0.250***	0.254***	0.242***	0.160***	0.196***
	(5.699)	(5.454)	(5.050)	(5.055)	(4.873)	(2.772)	(3.461)
DCOV_2B	0.268***	0.241***	0.221***	0.227***	0.217***	0.148**	0.131**
	(5.648)	(5.179)	(4.592)	(4.555)	(4.354)	(2.548)	(2.150)
LISTED			0.091	0.028	0.025	0.015	0.011
			(0.691)	(0.211)	(0.190)	(0.111)	(0.077)
BHC			0.109	0.126	0.113	0.109	0.086
			(0.839)	(0.970)	(0.877)	(0.857)	(0.676)
BIGAUD			0.150***	0.162***	0.169***	0.164***	0.172***
			(2.719)	(2.634)	(2.807)	(2.712)	(2.852)
OHRGTA				-0.004**	-0.002	-0.002	-0.002
				(-2.341)	(-1.083)	(-1.332)	(-1.241)
NDEPGTA				-0.009*	-0.009*	-0.009*	-0.008*
				(-1.846)	(-1.843)	(-1.879)	(-1.665)
IDIV				-0.002***	-0.002***	-0.002***	-0.002***
				(-3.290)	(-3.541)	(-3.564)	(-4.007)
FAGTA				0.014	0.017	0.018	0.022*
				(1.205)	(1.373)	(1.436)	(1.769)
LOANGTA				-0.001	-0.001	-0.001	-0.001
				(-0.533)	(-0.507)	(-0.534)	(-0.434)
LRGTA				0.507**	0.497**	0.497**	0.543***
				(2.561)	(2.499)	(2.477)	(2.695)
LRGTA SQ				-0.035**	-0.034**	-0.035**	-0.038**
				(-2.368)	(-2.262)	(-2.294)	(-2.511)
LERNER					0.250**	0.250***	0.302***
					(2.565)	(2.627)	(3.066)
EGROWTH						0.054***	0.037**
						(4.230)	(2.602)
DIRATE						-0.003	0.002
						(-0.387)	(0.303)
LN NBREG							0.007
							(0.817)
CRBREG							0.176***
							(3.080)

(Continued)

Table 3.3: Deposit Insurance Coverage and Bank Risk-Taking

	Dependent variable: *LN ZSCORE*						
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.403***	3.415***	3.364***	1.731**	1.588**	1.413*	1.234*
	(82.352)	(119.401)	(64.116)	(2.560)	(2.363)	(1.945)	(1.695)
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,241	4,241	4,066	4,020	3,977	3,977	3,971
R-squared	0.038	0.480	0.483	0.491	0.492	0.496	0.501
N-clusters (bank)	137	137	134	134	134	134	134

Table 3.4: Robustness Checks

This table presents a variety of robustness checks on how deposit insurance coverage affects bank risk-taking, controlling for bank-specific, macroeconomic, and bank regulation variables. **Panel A** column (1) excludes all banks owned by the central (national) government, column (2) excludes all banks owned by central and regional (province) governments, column (3) excludes Too-Big-To-Fail (TBTF) banks defined as 15 largest banks by GTA, column (4) clusters standard errors in two-way at the bank and quarter levels, column (5) controls for bank random effects instead of fixed effects, and column (6) add time trend and its squared term as additional controls. **Panel B** column (1) starts the sample period in 2006:Q1, excluding the blanket guarantee, transition, and full deposits guarantee periods, column (2) estimates the regression on the subsample period when there are no material changes in bank regulation (2006:Q1-2010:Q4), based on the World Bank surveys on bank regulation (Barth, Caprio, and Levine, 2013), column (3) conducts a placebo test by using all deposit insurance coverage indicators forwarded by 3 years, and column (4) conducts a placebo test by using all deposit insurance coverage indicators backwarded by 3 years. The base period used in Panel B is 2006:Q1 – 2006:Q2, i.e. when the government started to set a nominal maximum limit on deposit guarantee (an explicit deposit insurance coverage), which was IDR 5 billion. **Panel C** conduct robustness checks using alternative risk measures as follows: standard deviation of *ROE* over 4 quarters (*SDROE*), the ratio of nonperforming loans to total loans (*NPL/TL*), and the ratio of nonperforming assets to GTA (*NPA/GTA*). **Panel D** conducts robustness checks by extending the transition period from 2003:Q1-2005:Q2. I choose 2003:Q1 as the beginning of the extended transition period as the earliest news I find from Factiva about the phasing out of deposit insurance coverage up to IDR 100 million dated at January 30, 2003. As *LN ZSCORE* and *SD ROE* are calculated over 4 quarters, these measures start in 2002:Q4 and therefore, cannot be used in this extended transition regression setting. The sample covers all Indonesian commercial banks for the sample period mentioned in each panel. All financial ratios are winsorized at 1% level at the top and bottom, unless specified differently. All level financial variables are denominated in billions of Indonesian Rupiah (IDR), deflated using the year 2000 implicit GDP price deflator. All control variables are lagged at time $t-4$ if the dependent variable is measured over 4 quarters from time $t-3$ to t, and lagged at time $t-1$ if the dependent variable is measured at time t. Standard errors are clustered at the bank level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Numbers in parentheses are t-statistics.

Panel A: Robustness Checks

	Dependent variables: *LN ZSCORE*					
	Excluding CSOBs	Excluding CSOBs and RSOBs	Excluding TBTF Banks	Two-way Cluster	Random Effect	Controlling Time Trend
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)
DCOV_TR	0.028	0.019	0.041	0.023	0.017	0.016
	(0.562)	(0.316)	(0.762)	(0.504)	(0.338)	(0.339)
DCOV_FG	0.030	0.015	0.055	0.022	0.014	0.056
	(0.530)	(0.223)	(0.911)	(0.445)	(0.256)	(0.818)
DCOV_5B	0.048	0.047	0.058	0.036	0.022	0.099
	(0.834)	(0.691)	(0.940)	(0.759)	(0.387)	(1.299)
DCOV_1B	0.218***	0.244***	0.199***	0.209***	0.194***	0.342***
	(3.552)	(3.339)	(3.108)	(4.371)	(3.319)	(3.611)
DCOV_100M	0.189***	0.204***	0.167***	0.196***	0.184***	0.384***
	(3.262)	(2.945)	(2.718)	(3.811)	(3.328)	(3.272)
DCOV_2B	0.112*	0.099	0.139**	0.131**	0.127**	0.368***
	(1.786)	(1.337)	(2.084)	(2.176)	(2.131)	(2.622)

(Continued)

Table 3.4: Robustness Checks

Panel A: Robustness Checks

	Dependent variables: *LN ZSCORE*					
	Excluding CSOBs	Excluding CSOBs and RSOBs	Excluding TBTF Banks	Two-way Cluster	Random Effect	Controlling Time Trend
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)
TIME TREND						-0.021
						(-1.285)
TIME TREND SQ						0.000
						(0.677)
Bank nonfinancial controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank financial controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank competition control	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank regulation controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	No	Yes
Bank Random Effects	No	No	No	No	Yes	No
Observations	3,829	3,048	3,455	3,971	3,971	3,971
R-squared	0.509	0.495	0.513	0.501	0.110	0.501
N-clusters (bank)	130	105	122	134	134	134
N-clusters (quarter)				36		

(Continued)

Table 3.4: Robustness Checks

Panel B: Robustness Checks

	Dependent variables: *LN ZSCORE*			
	Baseline: 2006:Q1-2011:Q4	Subsample of when no material changes in bank regulation: 2006:Q1-2010:Q4	Placebo: 3 Years Forward (2009:Q1-2011:Q4)	Placebo: 3 Years Backward (2003:Q1-2005:Q4)
Independent variables:	(1)	(2)	(3)	(4)
DCOV_1B	0.162***	0.171***	-0.019	-0.021
	(3.626)	(3.738)	(-0.459)	(-0.308)
DCOV_100M	0.113**	0.121**	-0.050	-0.073
	(2.180)	(2.203)	(-0.590)	(-0.761)
DCOV_2B	0.088*	0.109*	-0.006	-0.059
	(1.724)	(1.954)	(-0.068)	(-0.340)
Bank nonfinancial controls	Yes	Yes	Yes	Yes
Bank financial controls	Yes	Yes	Yes	Yes
Bank competition control	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes
Bank regulation controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,479	2,076	1,145	1,492
R-squared	0.541	0.577	0.609	0.621
N-clusters (bank)	126	126	115	133

(Continued)

Table 3.4: Robustness Checks

Panel C: Robustness Checks

	Dependent variable:			
	LN ZSCORE	*SD ROE*	*NPL/TL*	*NPA/GTA*
Independent variables:	(1)	(2)	(3)	(4)
DCOV_TR	0.023	-1.172	-0.308	-0.088
	(0.462)	(-0.794)	(-0.957)	(-0.608)
DCOV_FG	0.022	-1.829	-0.615	-0.247
	(0.381)	(-1.117)	(-1.323)	(-1.046)
DCOV_5B	0.036	-1.832	-1.437***	-0.605**
	(0.613)	(-1.303)	(-2.669)	(-2.315)
DCOV_1B	0.209***	-3.067**	-1.592***	-0.604**
	(3.484)	(-2.048)	(-2.703)	(-2.008)
DCOV_100M	0.196***	-4.015**	-1.425***	-0.058
	(3.461)	(-2.134)	(-2.772)	(-0.181)
DCOV_2B	0.131**	-3.007*	-1.842***	-0.400
	(2.150)	(-1.721)	(-3.106)	(-1.086)
Bank nonfinancial controls	Yes	Yes	Yes	Yes
Bank financial controls	Yes	Yes	Yes	Yes
Bank competition control	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes
Bank regulation controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	3,971	3,971	4,445	4,445
R-squared	0.501	0.514	0.490	0.524
N-clusters (bank)	134	134	137	137

(Continued)

Table 3.4: Robustness Checks

Panel D: Robustness Checks

	Dependent variables:	
	NPL/TL	NPA/GTA
Independent variables:	(1)	(2)
DCOV_TR_E	-0.632	-0.266
	(-1.601)	(-1.261)
DCOV_FG	-1.069**	-0.464*
	(-2.368)	(-1.813)
DCOV_5B	-1.749***	-0.747***
	(-3.353)	(-2.725)
DCOV_1B	-1.957***	-0.771**
	(-3.438)	(-2.415)
DCOV_100M	-1.842***	-0.258
	(-3.688)	(-0.736)
DCOV_2B	-2.317***	-0.622
	(-3.946)	(-1.533)
Bank nonfinancial controls	Yes	Yes
Bank financial controls	Yes	Yes
Bank competition control	Yes	Yes
Macroeconomic controls	Yes	Yes
Bank regulation controls	Yes	Yes
Bank FE	Yes	Yes
Observations	4,447	4,445
R-squared	0.490	0.524
N-clusters (bank)	138	137

Table 3.5: Channels in which Deposit Insurance Coverage affects Bank Risk-Taking

This table presents the OLS regression estimates of LN ZSCORE's components on deposit insurance coverage indicator variables, controlling for bank-specific, macroeconomic, and bank regulation variables. Column (1) is the baseline regression using LN ZSCORE as the dependent variable, the same with column (7) of Table 3. Column (2), (3), and (4) use the mean profitability (MU ROA), standard deviation of profitability (SD ROA), and mean capitalization (MU EQ/GTA) as the dependent variable respectively. The sample covers all Indonesian commercial banks from 2002:Q1-2011:Q4. All financial ratios are winsorized at 1% level at the top and bottom, unless specified differently. All level financial variables are denominated in billions of Indonesian Rupiah (IDR), deflated using the year 2000 implicit GDP price deflator. All control variables are lagged at time $t-4$. Standard errors are clustered at the bank level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Numbers in parentheses are t-statistics.

	Dependent variables:			
	Baseline	*LN ZSCORE* components:		
	LN ZSCORE	*MU ROA*	*SD ROA*	*MU EQ/GTA*
Independent variables:	(1)	(2)	(3)	(4)
DCOV_TR	0.023	0.107	-0.140	-0.475
	(0.462)	(0.853)	(-1.304)	(-1.594)
DCOV_FG	0.022	-0.217*	-0.252**	-0.528
	(0.381)	(-1.657)	(-1.998)	(-1.247)
DCOV_5B	0.036	-0.360**	-0.380***	-0.300
	(0.613)	(-2.144)	(-3.066)	(-0.594)
DCOV_1B	0.209***	-0.294*	-0.481***	1.046**
	(3.484)	(-1.894)	(-3.974)	(1.982)
DCOV_100M	0.196***	-0.327***	-0.363***	1.951***
	(3.461)	(-2.781)	(-2.740)	(3.837)
DCOV_2B	0.131**	-0.445***	-0.209	3.576***
	(2.150)	(-2.717)	(-1.465)	(4.752)
Bank nonfinancial controls	Yes	Yes	Yes	Yes
Bank financial controls	Yes	Yes	Yes	Yes
Bank competition control	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes
Bank regulation controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	3,971	3,971	3,971	3,971
R-squared	0.501	0.666	0.451	0.844
N-clusters (bank)	134	134	134	134

Table 3.6: Optimum Range of Deposit Insurance Coverage

This table presents the OLS regression estimates of *LN ZSCORE*, *SD ROE*, *NPL/Tl*, and *NPA/GTA* on deposit insurance coverage indicator variables, controlling for bank-specific, macroeconomic, and bank regulation variables, using the IDR 1 billion coverage period (*DCOV_1B*) as the base. This strategy enables us to estimate the coefficient of deposit insurance coverage that is lower or higher than the base's coverage. **Panel A** estimates the regressions on the full sample from 2002:Q1-2011:Q4. **Panel B** estimates the regressions on the subsample period when there are no material changes in bank regulation (2006:Q1-2010:Q4), based on the World Bank surveys on bank regulation (Barth, Caprio, and Levine, 2013). All financial ratios are winsorized at 1% level at the top and bottom, unless specified differently. All level financial variables are denominated in billions of Indonesian Rupiah (IDR), deflated using the year 2000 implicit GDP price deflator. All control variables are lagged at time $t-4$. Standard errors are clustered at the bank level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Numbers in parentheses are t-statistics.

Panel A: Full Sample Regressions using *DCOV_1B* as the Base

	Dependent variables:			
	LN ZSCORE	*SD ROE*	*NPL/TL*	*NPA/GTA*
Independent variables:	(1)	(2)	(3)	(4)
DCOV_BG	-0.195***	2.386**	1.492***	0.575**
	(-4.208)	(2.273)	(2.795)	(2.064)
DCOV_FG	-0.191***	1.453	1.065***	0.381*
	(-3.649)	(1.631)	(2.964)	(1.739)
DCOV_5B	-0.178***	1.513*	0.138	-0.007
	(-3.943)	(1.839)	(0.668)	(-0.057)
DCOV_100M	-0.011	-1.059	0.248	0.569**
	(-0.306)	(-1.103)	(0.650)	(2.167)
DCOV_2B	-0.081	0.230	-0.183	0.223
	(-1.566)	(0.230)	(-0.351)	(0.679)
Bank nonfinancial controls	Yes	Yes	Yes	Yes
Bank financial controls	Yes	Yes	Yes	Yes
Bank competition control	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes
Bank regulation controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	3,971	3,971	4,445	4,445
R-squared	0.501	0.514	0.490	0.524
N-clusters (bank)	134	134	137	137

(Continued)

Table 3.6: Optimum Range of Deposit Insurance Coverage

Panel B: Regressions on the Subsample Period from 2006:Q1-2010:Q4

	Dependent variables:			
	LN ZSCORE	*SD ROE*	*NPL/TL*	*NPA/GTA*
Independent variables:	(1)	(2)	(3)	(4)
DCOV_5B	-0.171***	2.153***	0.054	-0.093
	(-3.738)	(3.241)	(0.240)	(-0.710)
DCOV_100M	-0.050	-0.004	-0.239	0.626**
	(-1.385)	(-0.004)	(-0.783)	(2.217)
DCOV_2B	-0.063	0.182	-0.513	0.414
	(-1.209)	(0.158)	(-1.475)	(1.397)
Bank nonfinancial controls	Yes	Yes	Yes	Yes
Bank financial controls	Yes	Yes	Yes	Yes
Bank competition control	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes
Bank regulation controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	2,076	2,076	2,202	2,202
R-squared	0.577	0.599	0.634	0.660
N-clusters (bank)	126	126	125	125

Table 3.7: Ownership Structure, Deposit Insurance Coverage, and Bank Risk-Taking

This table presents the OLS regression estimates of *LN ZSCORE* on deposit insurance coverage indicators and ownership variables for different type of ultimate shareholders, controlling for bank-specific, macroeconomic, and bank regulation variables. **Panel A** estimates the regressions on the full sample from 2002:Q1-2011:Q4. **Panel B** estimates the regressions on the subsample period from 2007:Q1-2011:Q4, so that we can focus on the impact of the latest increase in deposit insurance coverage from IDR 1 million to 20 billion. The government advocated the policy as a precautionary measure against the global financial crisis, following many other countries' similar responses. Column (1) shows the baseline regression estimates using all Indonesian commercial banks. Column (2) shows the regression estimates using the subsample of banks owned ultimately by foreign institutions. Column (3) shows the regression estimates using the subsample of banks owned ultimately by families or family-based business groups. Column (4) shows the regression estimates using the subsample of private banks with at least one of the commissioners, directors, or controlling shareholders is a current of former political party member, parliament member, or government official. Column (5) shows the regression estimates using the subsample of private banks that are not politically connected. Column (6) shows the regression estimates using the subsample of banks owned ultimately by foreign institutions that have political connections. Column (7) shows the regression estimates using the subsample of banks owned ultimately by families or family-based business groups that have political connections. All financial ratios are winsorized at 1% level at the top and bottom, unless specified differently. All level financial variables are denominated in billions of Indonesian Rupiah (IDR), deflated using the year 2000 implicit GDP price deflator. All control variables are lagged at time $t-4$. Standard errors are clustered at the bank level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Numbers in parentheses are t-statistics.

Panel A: Regression Estimates on the Full Sample from 2002:Q1-2011:Q4

	Dependent variable: *LN ZSCORE*						
	ALL BANKS	*UFOREIGN*	*UFAMILY*	*POLCON*	*NON POLCON*	*UFOREIGN * POLCON*	*UFAMILY * POLCON*
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DCOV_TR	0.025	0.083	-0.014	-0.007	0.021	-0.002	0.129
	(0.494)	(0.854)	(-0.146)	(-0.075)	(0.289)	(-0.013)	(1.023)
DCOV_FG	0.027	-0.064	0.078	0.073	-0.014	-0.130	0.243
	(0.455)	(-0.659)	(0.681)	(0.557)	(-0.176)	(-0.614)	(1.660)
DCOV_5B	0.046	0.061	0.109	0.157	-0.004	0.096	0.377**
	(0.774)	(0.636)	(1.076)	(1.132)	(-0.053)	(0.415)	(2.718)
DCOV_1B	0.214***	0.241**	0.340***	0.374**	0.179**	0.647**	0.618**
	(3.500)	(2.333)	(2.732)	(2.333)	(2.294)	(2.588)	(2.665)
DCOV_100M	0.208***	0.150	0.229**	0.351**	0.131*	0.515**	0.369**
	(3.509)	(1.541)	(2.211)	(2.500)	(1.724)	(2.294)	(2.127)
DCOV_2B	0.141**	0.017	0.211**	0.145	0.105	0.173	0.318**
	(2.133)	(0.143)	(2.021)	(1.009)	(1.086)	(0.617)	(2.226)
MANCF	-0.002	-0.009***	-0.002	-0.005**	0.001	-0.006	-0.004
	(-1.592)	(-2.692)	(-1.326)	(-2.551)	(0.335)	(-1.076)	(-1.624)
UCASH	-0.002	-0.002	-0.000	-0.001	-0.000	-0.003*	0.000
	(-1.544)	(-1.396)	(-0.157)	(-0.353)	(-0.297)	(-1.826)	(0.154)
WEDGE	-0.008	-0.019	-0.012***	-0.010	-0.003	-0.051***	-0.021**
	(-1.209)	(-1.270)	(-3.037)	(-0.524)	(-0.648)	(-5.506)	(-2.418)
Bank nonfinancial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank financial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Table 3.7: Ownership Structure, Deposit Insurance Coverage, and Bank Risk-Taking

Panel A: Regression Estimates on the Full Sample from 2002:Q1-2011:Q4

	Dependent variable: *LN ZSCORE*						
	ALL BANKS	*UFOREIGN*	*UFAMILY*	*POLCON*	*NON POLCON*	*UFOREIGN * POLCON*	*UFAMILY * POLCON*
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bank competition control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank regulation controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,927	1,279	1,238	1,101	1,942	342	539
R-squared	0.502	0.572	0.473	0.395	0.575	0.422	0.523
N-clusters (bank)	134	55	54	38	76	17	24

Panel B: Regression Estimates on the Subsample Period from 2007:Q1-2011:Q4

	Dependent variable: *LN ZSCORE*						
	ALL BANKS	*UFOREIGN*	*UFAMILY*	*POLCON*	*NON POLCON*	*UFOREIGN * POLCON*	*FAMILY * POLCON*
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DCOV_2B	-0.048	-0.149*	-0.042	-0.239***	0.006	-0.406**	-0.157
	(-1.068)	(-1.951)	(-0.456)	(-2.768)	(0.085)	(-2.759)	(-1.544)
MANCF	-0.007**	-0.011***	-0.004	-0.010	-0.004**	-0.009	-0.003
	(-2.597)	(-2.732)	(-1.187)	(-1.677)	(-2.162)	(-1.337)	(-0.617)
UCASH	-0.001	-0.001	-0.001	0.005*	-0.001	0.001	0.005
	(-0.473)	(-0.515)	(-0.315)	(1.808)	(-0.508)	(0.373)	(1.420)
WEDGE	-0.012	-0.023***	-0.017**	-0.015	-0.015***	-0.032**	-0.011
	(-1.297)	(-3.480)	(-2.129)	(-0.957)	(-3.365)	(-2.323)	(-1.130)
Bank nonfinancial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank financial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank competition control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank regulation controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,997	743	603	611	926	235	321
R-squared	0.566	0.608	0.552	0.445	0.664	0.395	0.578
N-clusters (bank)	123	49	45	37	65	17	24

CHAPTER 4

COMPETITION DOES NOT KILL BANKS; IT MAKES THEM STRONGER: THE IMPACT OF GEOGRAPHIC DEREGULATION ON BANK RISK[40,41]

"… we have deregulated the financial services sector, and we face another crisis."
Barack Obama, the U.S. President 2009-2017, *Renewing the American Economy*,
Presidential campaign speech at the Cooper Union, March 27, 2008,
http://www.presidency.ucsb.edu/ws/?pid=93292

"More than 30 years of deregulation and reliance on self-regulation by financial institutions, … stripped away key safeguards, which could have helped avoid catastrophe."
The U.S. Financial Crisis Inquiry Commission, *Final Report of the National Commission on the Causes of the Financial and Economic Crisis in the United States*,
The Financial Crisis Inquiry Report, January 2011, p. xviii.

4.1 INTRODUCTION

Bank deregulation is a very controversial subject, particularly since the recent financial crisis. The traditional economic literature suggests that competition benefits the society by encouraging firms to provide better service, lower price, and promote more innovation (e.g. Kovacic and Saphiro, 2000; Aghion, Bloom, Blundell, Griffith, and Howitt, 2005). Motivated by this view, during 1970s-1980s and in the first half of the 1990s, U.S. states relaxed restrictions on the geographic expansion of banks gradually. This geographic deregulation, in which banks have been allowed to offer services on an expanded basis within and across states, started the deregulation era in the U.S. banking

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industry after the Great Depression and play major roles in the changing structure of the U.S. banking industry, leading to the next era of nationwide banking (Berger, Kashyap, Scalise, Gertler, and Friedman, 1995; Jeon and Miller, 2003; Stiroh and Strahan, 2003; Strahan, 2003). For this reason, among others, this deregulation is popular in finance research. Moreover, the timing of the deregulation between each state is different and therefore, it provides a unique setting to conduct a quasi-natural experiment study.

Most of the empirical studies suggest positive effects of the deregulation on bank customers and the real economy. For example, the deregulation is found to be associated with higher real per capita income growth (Jayaratne and Strahan, 1996; Clarke, 2004; Huang, 2008), higher entrepreneurial activity (Black and Strahan, 2002; Strahan, 2003), greater real investments (Zarutskie, 2006), more start-up firms (Kerr and Nanda, 2009), increased credit supply to businesses (Rice and Strahan, 2010; Chu, 2016) and to households (Dick and Lehnert, 2010), more efficient resource allocation (Bai, Carvalho, and Phillips, 2015), higher externally-financed firm growth (Berger, Chen, El Ghoul, and Guedhami, 2016), greater firm productivity (e.g., Krishnan, Nandy, and Puri, 2014), more home ownership (e.g., Tewari, 2014), and reduction of income inequality (Beck, Levine, and Levkov, 2010). The only research area in which the results are mixed is innovations by nonfinancial firms, for which most of the research suggests favorable results from interstate deregulation in which banks are allowed to cross state lines (e.g., Amore, Schneider, and Žaldokas, 2013; Chava, Oettl, Subramanian, and Subramanian, 2013; Cornaggia, Mao, Tian, Wolfe, 2015), and mostly unfavorable results from intrastate deregulation in which banks are allowed more freedom to locate offices within states (e.g., Chava, Oettl, Subramanian, and Subramanian, 2013; Cornaggia, Mao, Tian, Wolfe, 2015; Hombert and Matray, 2016). A more limited amount of research suggests customer benefits from deregulation that allowed commercial banking organizations to enter investment banking (e.g., Drucker and Puri, 2005).[42]

However, doubts remain about the risks created by bank deregulation. As seen in the quotes above, policymakers and politicians, as well as much of the public, believe that deregulation increases bank risk to the point of being largely responsible for the recent financial crisis. Moreover, small banks opposed the deregulation with the fear that an increase in competition from large banks could reduce their survival probability (e.g. Economides, Hubbard, and Palia, 1996; Kroszner and Strahan, 1999). Surprisingly, there are still limited research efforts on this aspect of deregulation. Moreover, to our knowledge, no complete picture yet has emerged from the literature on how bank deregulation affects risk and this paper aims to begin filling this hole. We examine the intrastate branching and interstate banking deregulation by the U.S. states from 1984:Q1-1994:Q3, as well as the deregulation from 1994:Q4-2013:Q4 of the remaining state restrictions allowed by the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA), which allowed interstate branch banking for the first time since the 1927 McFadden Act. Further, we examine different channels in which the deregulation affects bank risk and analyze whether the impacts are different on small banks compared to medium and large banks to shed light on whether the small banks' early fear on the deregulation materializes.

We start our main analysis using all U.S. commercial banks between 1984:Q1 and 1994:Q3, when most of the intrastate branching and interstate banking deregulation

[42] See Berger and Roman (forthcoming) for a more complete summary of the effects of bank deregulation on the U.S. economy.

occurred at the state level. Intrastate branching deregulation allows banks to open branches statewide, while interstate banking deregulation permits bank acquisition by out-of-state banks. We stop the sample period in 1994:Q3 to avoid any confounding effect of the Riegle-Neal Act that was signed by President Bill Clinton on September 29, 1994. Then, we study the interstate branching deregulation, in which banks are allowed to have interstate branches, from 1994:Q4-2013:Q4. To test the relation between bank deregulation and risk pre-the Riegle-Neal Act, we run panel regression models with the generalized Difference-in-Difference (DID) specification. The main dependent variable is the natural logarithm of bank *Z-Score* (*Ln Z-Score*), an inverse indicator of bank insolvency risk. The explanatory variables are two indicator variables of the intrastate branching and interstate banking deregulation. Post-the Riegle-Neal Act, we regress *Ln Z-Score* on the interstate branching restriction index developed by Rice and Strahan (2010).

In summary, we find strong evidence that the interstate banking deregulation is associated with lower bank risk. The regression coefficient on *Ln Z-Score* is about 0.237, which means that on average, banks in states allowing bank acquisition by out-of-state banks have 26.7% higher *Z-score* than banks in states prohibiting it. However, we do not find significant evidence that the interstate branching deregulation affects bank risk, suggesting that interstate merger and acquisition activities provide stronger incentives to alter bank risk compared to the interstate branching. Meanwhile, we find mixed evidence on the impact of intrastate branching activities on bank risk. These results are robust to various sensitivity checks, including analyses to address reverse causality, omitted variables, and sample selection concerns.

To mitigate an endogeneity problem due to the possible reverse causality between deregulation and bank risk, we run instrumental variables (IV) regressions using deregulation variables of adjoining states as the instruments. To address a possible omitted variable bias, first, we control for lagged state population density, bank size, Bank Holding Company (BHC) membership, publicly listed status, local market concentration, asset diversification, overhead costs ratio, internationalization activities, as well as time (quarter) and bank fixed effects in our main specification. Then, we conduct a contiguous-county matching following Huang (2008). This contiguous-county matching also addresses the sample selection concern. As all our analyses suggest that interstate branching deregulation has no impact on bank risk, we focus the rest of our analyses on the intrastate branching and interstate banking deregulation.

To mitigate the concern that the dynamics of the U.S. banks' entry and exit may confound our main results, we run a further robustness check using a balanced sample that excludes new entrant banks and banks that exit the industry during the sample period. In addition, we run other robustness checks including regressions using two-way cluster standard errors and bootstrapped standard errors, placebo test, as well as regressions that exclude two states with very different banking regulations (Delaware and South Dakota), too-big-too-fail banks, and regression at the BHC level. Finally, we run our regressions using alternative risk measures. Our main results continue to hold to all these sensitivity analyses.

To test the channels that can explain our main findings, we firstly run our main regressions in densely and sparsely populated states. We construct a population density variable defined as population per square mile. Previous studies such as Akhigbe and

Whyte (2003), Deng and Elyasiani (2008), and Goetz, Laeven, and Levine (2016) show that banks benefit from diversification as they expand their market geographically. We find that intrastate branching reduces bank risk in densely populated states. As these states are mainly served by large banks that have more diversification capacity than small banks, this finding sheds light on the ***Diversification-Stability Channel***. On the other hand, in sparsely populated states where small banks play more important role than in densely populated states, statewide branching expansion is associated with higher risk. This finding sheds light on the ***Diversification Monitoring Channel*** as small banks might face greater difficulties in monitoring their expanded number of intrastate branches compared to large banks. Meanwhile, our finding on interstate banking deregulation shows that this reform is associated with risk reduction in sparsely populated states but not in densely populated states. As allowing bank acquisitions by out-of-state banks increases the local market contestability by increasing takeover threats (Dick and Lehnert, 2010), this threat pushes banks in sparsely populated states, that are dominated by small banks, to operate more efficiently and therefore, reduces their insolvency risk. This finding is consistent with the ***Competition-Stability Channel***. Meanwhile, in densely populated states that have more large banks, this takeover threat is less effective as acquiring them is costlier than small banks. Besides, as the intrastate branching had mostly occurred before the interstate banking deregulation, large banks might have utilized the statewide branching expansion to increase their size to defend themselves from takeover by out-of-state banks. The results are consistent when we run our regressions for subsample of small, medium, and large banks.

We organize the remainder of this paper as follow. Section 4.2 provides a literature review. Section 4.3 describes the data, variables, and summary statistics. Section 4.4 presents the main empirical results. Section 4.5 presents endogeneity checks. Section 4.6 provides robustness checks of the main empirical results. Section 4.7 presents analysis on the competition channel to explain the main results. Section 4.8 concludes the paper.

4.2 RELATED LITERATURE

From the end of the Great Depression, which caused thousands of bank defaults, until the early 1970s, most states in the U.S. imposed restrictions on statewide branching (either full "unit banking" or partial "limited branching") ostensibly to protect local and small banks from the threat of competition from large banks. In addition to the intrastate (statewide) branching restriction, the Douglas Amendment to the 1956 Bank Holding Company Act prohibited a BHC from acquiring banks outside the state where it was headquartered unless the target bank's state permitted such actions. Though the states could allow out-of-state BHCs to enter, all states chose to prohibit the interstate bank expansion until 1978 when Maine became the first to allow acquisitions of its in-state banks by out-of-state BHCs. During the next two decades (the 1970s and 1980s), many states relaxed the restrictions on intrastate branching and interstate banking activities. By 1993, only Arkansas and Iowa still DID not fully allow intrastate branching activities, and only Hawaii still prohibited interstate banking activities.[43] The next and final era of deregulation on bank geographic expansion started in 1994 when the U.S. government

[43] Arkansas lifted fully the interstate branching restriction in 1994 and Iowa in 1999. Hawaii allowed interstate banking activities in 1997. See Kroszner and Strahan (1999) and Francis, Hasan, and Wang (2014) for more details on the timing of the intrastate branching and the interstate banking deregulation.

passed the Riegle-Neal IBBEA. The Riegle-Niel Act allowed unrestricted interstate banking (effective in 1995) and legalized interstate branching in all U.S. states (effective in 1997).[44] After this law was enacted, banks or BHCs could either open new branches in other states or convert their subsidiaries in other states into operational branches. Therefore, this deregulation is mainly a more advanced step of the interstate banking deregulation.

A few papers have studied the impact of the geographic expansion deregulation on bank risk and the empirical results found are mixed. Jayaratne and Strahan (1996) study state-level data of all commercial banks from 1976 to 1992 and find that the intrastate branching deregulation is associated with lower credit risk. Using the same state-level data, Jayaratne and Strahan (1998) find similar results for the interstate banking deregulation, but to a lesser extent than the impact of the intrastate branching deregulation. Rose (1996) examines a sample of 84 large U.S. BHCs from 1980–1992 and find some evidence that interstate banking expansion leads to higher risk. However, Rose shows that some diversification gains emerge when banks expand to at least four states. Rivard and Thomas (1997) study 218 BHCs' data from 1988–1991 and find that interstate BHCs have higher profitability, lower earnings volatility, and lower insolvency risk compared to strictly intrastate banks. Carlson and Mitchener (2006) examine earlier state-level national banks' data from 1922–1930 (the Great Depression era) and find that intrastate branching activities lead to tougher competition, which results in improvement of the banking system stability by removing weak and inefficient banks. Dick (2006) study the impacts of the Riegle-Niel interstate branching deregulation from 1993–1999

[44] However, the law permitted the states to take advantage of several provisions to slow down the growth of incoming interstate branching activities. For more details, see Rice and Strahan (2010).

and finds that the deregulation leads to higher credit portfolio risk. Subramanian and Yadav (2012) examine the impact of the intrastate branching and the interstate banking deregulation on bank failures from 1976–1994. They find that intrastate branching deregulation leads to fewer bank failures (especially in the unit banking states) due to more portfolio diversification, operating efficiencies, and reduced loan losses. However, they find no evidence that interstate banking deregulation affects bank failures. Goetz, Laeven, and Levine (2016) develop a new instrument to identify exogenous sources of variation in geographic diversity at the BHC level and use it to examine the impact of BHC geographic expansion (in response to interstate banking deregulation) on BHC risk. Using the data of listed BHCs from 1986:Q2-1997:Q4, they find that BHC geographic expansion is associated with lower BHC risk. However, BHC geographic diversification has no significant impact on BHC loan quality.

Theoretically, there are at least three channels through which geographic deregulation may increase risk and at least two channels through which risk may reduce, making the net effect an empirical question. Turning to the first risk-increasing channel, **the *Hubris Channel***, deregulation provides opportunities for bank managers to expand their businesses geographically and gain higher salaries and/or more resources under their control to extract for their private benefits (e.g. Jensen, 1986; Berger and Ofek, 1995; Servaes, 1996; Denis, Denis, and Sarin, 1997; Laeven and Levine, 2007, Berger, El Ghoul, Guedhami, and Roman, forthcoming). Under **the *Diversification Monitoring Channel***, the geographic diversification raises more difficulty for the banks in monitoring their loans and managing their risks because of both increased complexity and distances between branches or subsidiaries (e.g. Winton, 1999; Berger and DeYoung, 2001;

Brickley, Linck, and Smith, 2003; Berger, Miller, Petersen, Rajan, and Stein, 2005). Finally, under the traditional ***Competition-Fragility Channel***, bank deregulation that leads to more competition in the local market, which may increase bank risk. Specifically, tougher competition erodes banks' profit margins and results in reduced franchise values, reducing incentives for the banks to control their risks to protect these values (e.g. Keeley, 1990; Hellmann, Murdock, and Stiglitz, 2000; Repullo, 2004).

Under the first risk-reducing channels, under **the *Diversification-Stability Channel***, bank deregulation provides an opportunity for banks to diversify their assets and widen their depositor bases, thereby reducing bank risk (e.g. Gart, 1994; Hubbard, 1994; Meslier-Crouzille, Morgan, Samolyk, and Tarazi, 2015; Goetz, Laeven, and Levine, 2016). Such diversification is an important part of the risk-transformation function of banks under modern portfolio theory (e.g., Diamond, 1984; Boyd and Prescott, 1986). Under the second risk-reduction channel, **the *Competition-Stability Channel***, bank deregulation intensifies competition in local markets (e.g. Jayaratne and Strahan, 1996; Carlson and Mitchener, 2006; Kerr and Nanda, 2009; Beck, Levine, and Levkov, 2010). More competition in the loan market reduces loan interest rates, which reduces borrower moral hazard and adverse selection problems (e.g. Boyd and De Nicolo, 2005; Boyd, De Nicolo, and Jalal, 2006; Akins, Li, Ng, and Rusticus, 2016).

4.3 DATA, VARIABLES, AND SUMMARY STATISTICS

4.3.1 DATA AND SAMPLE

Our bank-level financial datasets are from the quarterly Call Reports (*Reports of Condition and Income*) and cover all commercial banks in the U.S. from 1984:Q1 to

2013:Q4. The Call Reports start with 1976:Q1, but we choose the sample from 1984:Q1 since many banks prior to this have semiannual reports rather than quarterly. In particular, we observe there are 205,034 from 485,140 bank-quarter observations (42.26%) with missing net income (RIAD4340) in either Q1 or Q3 but not in Q2 and Q4.[45] Due to the lag structure of our baseline model, our main measure of bank risk starts from 1986:Q4. We divide our sample period into two subsamples. The first subsample period is from 1984:Q1 – 1994:Q3. This is the period when most of the intrastate branching and interstate banking deregulation occurred at the state level. We stop at 1994:Q3 for this subsample to avoid any confounding effect from the Riegle-Neal Act that was enacted in the fourth quarter of 1994 (September 29). The second subsample period is from 1994:Q4 – 2013:Q4. In this period, we focus the analysis only on the interstate branching deregulation.

The sample starts with 364,812 bank-quarter observations from the first subsample and 604,334 bank-quarter observations from the second subsample. We exclude non-commercial banks (RSSD9331 not equal to 1) as well as observations with zero or negative gross total assets (GTA),[46] total loans and leases, and total deposits. These filters leave us with 303,207 bank-quarter observations for 12,987 commercial banks for the first subsample, and 519,817 bank-quarter observations for 11,964 commercial banks across 50 U.S. states and the District of Columbia (DC). We deflate all U.S. dollars nominated variables using the 2010:Q4 GDP implicit price deflator[47] and

[45] Bluedorn, Bowdler, and Koch (2013) also identify this irregularity in the Call Reports, though they do not give further details on it.
[46] Gross total assets add back allowance for loan and lease losses (RCFD3123) and the allocated transfer risk reserves (RCFD3128) to each bank's total assets (RCFD2170) in order to measure the full value of the bank's assets financed. Hereinafter, we use assets and GTA interchangeably.
[47] The GDP implicit price deflator is downloaded from the Federal Reserve Bank of St. Louis' website: https://research.stlouifed.org/fred2/ /series/USAGDPDEFQISMEI.

winsorize all financial ratios at the 1% level on the top and bottom of their distributions to mitigate the impact of outliers.[48]

4.3.2 BANK RISK MEASURES

Our main measure of bank risk is *Z-Score*, which is an inverse measure of a bank's insolvency probability (e.g. Hannan and Hanweck, 1988; Laeven and Levine, 2009; Houston, Lin, Lin, and Ma, 2010; Beltratti and Stulz, 2012).[49] We calculate a bank's *Z-Score* as follow:

$$\textit{Z-score}_{i,t-k+1,t} = \frac{\mu_{i,t-k+1,t}(ROA) + \mu_{i,t-k+1,t}(Equity/GTA)}{\sigma_{i,t-k+1,t}(ROA)} \quad (1)$$

where $\mu_{t-k+1,t}(ROA)$ is the bank i's mean return on assets, calculated as net income over GTA, $\mu_{t-k+1,t}(Equity/GTA)$ is the bank i's mean capitalization ratio, and $\sigma_{t-k+1,t}(ROA)$ is the bank i's standard deviation of ROA. The mean and standard deviation are computed from time $t-k+1$ to time t. Following a methodology similar to Berger, El Ghoul, Guedhami, and Roman (2016), we use $k = 12$ quarters. A higher *Z-score* indicates that the bank has lower insolvency risk.

Rather than using the level of *Z-Score*, we follow Laeven and Levine (2009), Houston, Lin, Lin, and Ma (2010), and Beck, Jonghe, and Schepens (2013) and use the natural logarithm of *Z-Score* to reduce skewness in the distribution.[50] Since the *Z-Score* can take negative values, we employ the following *Ln* transformation to avoid truncations on negative values:

[48] We get equivalent results when we winsorize the financial ratios at 3% rather than 1% level.
[49] A bank is insolvent when its losses exhaust its capital (Hannan and Hanweck, 1988).
[50] Table 4.1 Panel B and C shows that the skewnesses of *Z-Scores* are greatly reduced from 1.687 to -0.389 and from 1.284 to -0.575 respectively when we use the natural logarithm transformation. results are similar when we use the level rather than the ln-transformed Z-score.

$$Ln\ Z\text{-}Score_{i,t-k+1,t} = \ln\left\{1 + \left|\min_{\forall i,t} Z_{i,t-k+1,t}\right| + Z_{i,t-k+1,t}\right\} \quad (2)$$

where $\left|\min_{\forall i,t} Z_{i,t-k+1,t}\right|$ is the global minimum of *Z-Score* from all bank-quarter observations over the sample period. This transformation will convert the global minimum (negative) value of *Z-Score* to zero.

We also conduct robustness checks using alternative measures of risk including the ratio of Commercial and Real Estate Loans to Total Loans (*CREL/TL*), Loan Portfolio Concentration (*LPC*), NPL ratio (*NPL/TL*), Cost-Income Ratio (*CIR*), and standard deviation of ROA (*SDROA*). CRE loans are considered to be the riskiest loan category and had a substantial contribution to the previous banking crisis (Cole and White, 2012). *LPC* is measured as $\sum_{n=1}^{5} LS_{nit}^{2}$, following Demsetz and Strahan (1997) and Berger, Bouwman, Kick, and Schaeck (2016), where LS_{kit} is the ratio of loan category n of bank i at time t to total loans. There are five loan categories (k) included, i.e. commercial and industrial loans, personal loans, commercial real estate loans, residential real estate loans, and other loans. This measures lies between 0 and 1, in which higher value indicates higher loan concentration. The more concentrated loans portfolio implies less diversification and is associated with higher bank risk. *NPL/TL* measures a bank's credit risk, calculated as the ratio of nonperforming loans to total loans.[51] *CIR* is calculated as the ratio of overhead expenses to gross revenues, following Beck, Demirgüç-Kunt, and Levine (2010). This variable measures how efficient a bank can manage its cost. The higher value of *CIR* indicates lower cost efficiency, which can lead to a higher likelihood of bank insolvency. *SDROA* is calculated as the standard deviation of bank ROA. This

[51] Nonperforming loans are loans that are past due at least 90 days or in nonaccrual status (RCFD1403 + RCFD1407).

variable captures the volatility of bank profitability. The higher value of *SDROA* implies higher risk. Similar with the *Ln Z-Score*, we measure this variable over 12 quarters.

4.3.3 BANK DEREGULATION

Our key variables of interest in the first subsample period from 1984:Q1 – 1994:Q3 are two indicator variables of intrastate branching deregulation ($Intra_{jt}$) and interstate banking deregulation ($Inter_{jt}$). $Intra_{jt}$ equals one if a bank is headquartered in a state j that has passed an intrastate branching deregulation by time t, and zero otherwise. $Inter_{jt}$ equals one if a bank is headquartered in state j that has passed an interstate banking deregulation by time t, and zero otherwise. We include all 50 U.S. states and DC in our analysis.[52] The deregulation years of the intrastate branching and interstate banking activities are from Amel (1993), Berger, Kashyap, and Scalise (1995), and Francis, Hasan, and Wang (2014).

In the second subsample period from 1994:Q4 – 2013:Q4, our variable of interest is the interstate branching restrictiveness index (*RSI*) that is constructed based on Rice and Strahan (2010). This index lies ranges from 0 (no restriction) to 4 (fully restricted), and therefore, is an inverse measure of bank deregulation. This index is a sum of indicator variables on state restrictions on minimum bank age, de novo branching, branch acquisition, and deposit cap related to interstate branching. In particular, each of the indicator variables is equal to 1 if a state imposes a minimum age of 3 or more years on target banks of interstate acquirers, does not permit de novo interstate branching, does not

[52] Some previous literature on U.S. bank deregulation excludes Delaware and South Dakota from the analysis because banks in these states had special tax incentives for credit card business (e.g. Black and Strahan, 2002; Dick and Lehnert, 2010; Amore, Schneider, and Zaldokas, 2013). Our results are still robust if we exclude these two states from the analysis (see Table 4 Panel B).

permit the acquisition of individual branches or portions of banks by an out-of-state bank, or if the state imposes a deposit cap less than 30 percent, and 0 otherwise. We update the data from Rice and Strahan (2010) using the Profile of State-Chartered Banking (PSCB) and State Banking Laws.[53] We also update the index following the Section 613 of the Dodd-Frank Act that effectively removes the restriction on de novo interstate branching.[54]

4.3.4 CONTROL VARIABLES

In order to mitigate a potential omitted variable bias, we control for various bank-specific and state economic condition variables, as well as bank fixed effects and time (quarters) fixed effects.[55] First, we control for state *population density*, which is measured by the ratio of each state's population to each state's area. Both of the U.S. state population and area datasets are from the U.S. Census Bureau. The economic literature shows a positive relation between population density and economic potentials (e.g. McGranahan and Beale, 2002; Walser and Anderlik, 2005). Accordingly, we may expect that banks having main businesses in sparsely populated areas are riskier for at least three reasons. First, it is difficult for the banks to achieve economies of scale due to limited bank customers. Second, the banks face more severe adverse selection problem due to the limited pools of potential borrowers. Finally, banks might find it difficult to diversify their loan portfolios due to lack of business diversity in the areas.

[53] These documents are available by a request to the Conference of State Bank Supervisors (CSBS) and from http://law.justia.com/. If there is any difference on interstate branching restriction between these document sources and Rice and Strahan (2010), we follow Rice and Strahan.
[54] In particular, we put 0 on the indicator variable of the de novo interstate branching for all states starting from 2010:Q4 onward.
[55] As bank capitalization ratio is one of the components used to construct our main risk measure, *Ln Z-Score*, we do not include this variable as one of the control variables in the right-hand-side of the regression.

Second, we control for *Housing Price Index (HPI)* measured by *Ln HPI*, which proxies the state economic condition. Third, we control for *bank size*. Prior studies show that bank size can affect risk. On the one hand, larger banks have more ability to diversify risks (e.g. Demsetz and Strahan, 1997; Deng and Elyasiani, 2008) and have more stable earnings (De Haan and Poghosyan, 2012a, b), and therefore, are more financially stable. On the other hand, larger banks may take more risks to benefit from the "too-big-to-fail" subsidies (e.g. O'Hara and Shaw, 1990; Boyd and Gertler, 1994; Laeven, Ratnovski, and Tong, 2014). To capture a possible nonlinear relation between bank size and risk (De Haan and Poghosyan, 2012a), we employ both *Ln GTA* and its squared term as proxies for bank size.

Fourth, we control for membership of a *Bank Holding Company (BHC)*. Several studies show that banks benefit from the support provided by their parent BHCs via internal capital markets (e.g. Houston, James, and Marcus, 1997; Ashcraft, 2008; Haas and Lelyveld, 2010). Other studies show that BHCs are associated with lower risk due to diversification (e.g. Deng and Elyasiani, 2008). However, there is a strand of literature that shows BHCs are associated with an increase in risk. For example, Demsetz and Strahan (1997) documents that the diversification benefit in large U.S. BHCs is offset by lower capitals and riskier loan portfolios. Similarly, Laeven and Levine (2007) shows that BHCs suffer from a diversification discount, which is related to intensified agency problems within the conglomerates. Following Berger, El Ghoul, Guedhami, and Roman (2016), we use a dummy variable that equals one if a bank is part of a BHC, and zero otherwise, as the proxy of BHC membership.

Fifth, we control for publicly *Listed* banks. On the one hand, publicly listed banks might be relatively safer than privately owned banks due to the greater degree of market discipline (Barry, Lepetit, and Tarazi, 2011). In particular, listed banks are subject to monitoring by capital market participants and capital market regulators, in addition to bank regulators. On the other hand, listed banks are generally larger and might be more likely to be bailed out due to their importance to financial markets. This provides incentives for listed banks to take more risk. We employ a dummy variable that equals one if a bank is publicly listed or is part of a publicly listed BHC and zero otherwise.

Sixth, we control for *local market concentration*. The literature shows that concentration can affect bank risk negatively or positively, depending on whether concentration-stability (e.g. Allen and Gale, 2000, 2004; Beck, Demirgüç-Kunt, and Levine, 2006; Craig and Dinger, 2013) or concentration-fragility (e.g. Boyd and De Nicolo, 2005; Boyd, De Nicolo, and Jalal, 2006) nexus holds.[56] Following prior studies (e.g. Berger, Demsetz, and Strahan, 1999; Cetorelli and Strahan, 2006), we use the *Herfindahl-Hirschman Index* (*HHI*) of deposits as the proxy for local market concentration.[57] Following Berger, Klapper, and Turk-Ariss (2009), we also include the squared term of HHI of deposits to capture a possible nonlinear relation between local market concentration and bank risk. We define a local banking market at Metropolitan Statistical Area (MSA) or New England County Metropolitan Area (NECMA) level and at the county level for non-MSA/NECMA rural counties. For each MSA/NECMA and

[56] Recent studies on bank competition such as Berger, Demirgüç-Kunt, Levine, and Haubrich (2004), Claessens and Laeven (2004), Beck, Demirgüç-Kunt, and Levine (2006), and Schaeck, Cihak, and Wolfe (2009) show that market concentration and competition are two different measures of banking market characteristics.

[57] For many years, the U.S. Department of Justice has been relying on the HHI measure as one of the main ways to evaluate each bank merger proposal. For more details see Berger, Demsetz, and Strahan (1999) and the *Horizontal Merger Guidelines* (U.S. Department of Justice and Federal Trade Commission, 2010).

non-MSA/NECMA rural county, we calculate HHI as the sum of squared-deposit shares of all banks and bank branches within the area for each period. We use bank deposits data from the *FDIC Summary of Deposits* (*SOD*).[58] To obtain HHI at the bank level, we calculate a bank's HHI as the deposit-weighted average of HHIs in all markets where the bank operates. For example, if a bank operates in five different MSAs and five non-MSA rural counties, then the bank's HHI is the sum of weighted HHIs for all of these ten local markets. The weight factor used for each local market is the bank's deposit in each market divided by the bank's total deposits in all of the ten local markets.

Seventh, we control for *diversification in banking activities.* The literature provides conflicting predictions on how diversification of business activities can affect bank risk. On the one hand, having two or more business activities that are not perfectly correlated may reduce the variability of a bank's cash flows. As such, the bank can still fund a positive NPV project regardless of the general condition of the economy and, therefore, has a lower financial risk (e.g. Froot, Scharfstein, and Stein, 1993; Froot and Stein, 1998). On the other side, more exposure to activities that generate noninterest income may potentially increase the bank risk due to monitoring complexity or intensified agency problems (e.g. Acharya, Hasan, and Saunders, 2006; Stiroh, 2006; Stiroh and Rumble, 2006; Laeven and Levine, 2007). Following Laeven and Levine

[58] The Summary of Deposits (SOD) data from 1994 onward are available from the FDIC's website at https://www5.fdic.gov/sod/dynaDownload.asp?barItem=6. We thank Christa Bouwman and Raluca Roman for sharing the SOD data prior to 1994. The FDIC gathers the data once a year through an annual survey of branch office deposits as of June 30.

(2007), we measure diversification in banking activities using the *asset diversification ratio*, which is calculated as $1-\left|\frac{\text{Net loans-Other earning assets}}{\text{Total Earning Assets}}\right|$.[59]

Eighth, we control for *overhead cost ratio*, which measures a bank's operating cost structure. DeYoung and Roland (2001) show that reliance on noninterest income is associated with an increase in a bank's degree of operating leverage, which transforms revenue volatility into higher earnings volatility. Similarly, Demirgüç-Kunt and Huizinga (2010) find that banks with high overhead costs tend to have higher insolvency risks. We measure the *overhead cost ratio* as the ratio f total overhead expenses to GTA, following Demirgüç-Kunt and Huizinga (2010). Total overhead expenses (RIAD4093) consist of personnel expenses (RIAD4135) and nonpersonnel expenses (RIAD4217 and RIAD4092).

Finally, we control for *bank internationalization* that is proxied by the ratio of a bank's *foreign assets to GTA*, following Berger, El Ghoul, Guedhami, and Roman (2016). On the one hand, an expansion of banking activities internationally might reduce bank risk due to the greater asset portfolio diversification (e.g. Laeven and Levine, 2007). However, the internationalization of banking activities can also increase bank risk due to market-specific factors (Berger, El Ghoul, Guedhami, and Roman, 2016), difference in local culture (Li and Guisinger, 1992; Berger, Li, Morris, and Roman, 2017), and difficulties in monitoring (Berger, De Young, Genay, and Udell, 2000).

[59] The main results are robust when we replace the *asset diversification ratio* with *income diversification ratio*, which is calculated as $1-\left|\frac{\text{Net interest income-Other operating income}}{\text{Total Operating Income}}\right|$.

4.3.5 SUMMARY STATISTICS

Tables 4.1 presents definitions (Panel A) and summary statistics of our variables (Panel B and C). In the first subsample period, the U.S. commercial banks have a mean *Ln Z-Score* of 3.0 and *Z-Score* of 26.3, indicating that on average the banks are fairly stable. In the second subsample period after the Riegle-Neal Act, the mean *Ln Z-Score* increases to 3.4 (*Z-Score* increases to 39.7), which implies that on average, U.S. banks have become relatively more stable. Similarly, the mean of *NPL/TL* and *SDROA* decreases from 2.3 percent to 1.1 percent and from 0.8 percent to 0.6 percent respectively in the second subsample period compared to the first subsample period. In terms of loan concentration, the mean of *LPC* before and after the Riegle-Neal Act are relatively stable, with the mean of about 0.3. However, the concentration of *CRE* loans increases almost two folds after the Riegle-Neal Act, from 12.2 percent to 21 percent. Moreover, the mean of banking cost efficiency, *CIR*, increases from 35 percent to 46.1 percent.

Meanwhile, in terms of bank characteristics, pre-the Riegle-Neal Act, U.S. banks have a mean size (*Gross Total Assets*) of $441 million, *HHI of deposits* of 0.08, *Asset Diversification* ratio of 28.3 percent, *Overhead Cost* ratio of 3.3 percent, and *Foreign Assets to GTA* ratio of 0.08 percent. Moreover, about 68 percent of the banks are part of Bank Holding Companies (BHCs) and 6.9 percent are listed or part of listed BHCs. Post-the Riegle-Neal Act, the banks have a mean size of $1 billion, *HHI of deposits* of 0.09, *Asset Diversification* ratio of 54.6 percent, *Overhead Cost* ratio of 3.2 percent, and *Foreign Assets to GTA* ratio of 0.06 percent. Furthermore, about 79 percent of the banks are part of BHCs and 12 percent are listed or part of listed BHCs. These imply that post the Riegle-Neal Act, U.S. banks are relatively bigger in size, have more diversified assets, and slightly better in overhead cost management as well as reduced international banking activities. The banking market is also more consolidated as the number of BHCs largely increases and more banks participation in the stock market. However, the local market concentration as measured by the HHI does not seem changed substantially after the Riegle-Neal Act. This finding extends the result in Black and Strahan (2002), which shows that HHI in local banking markets remains relatively constant despite the deregulation in geographic expansion in banking activities during 1976-1994. This is also in line with the result in Dick (2006) that finds no evidence that the interstate branching deregulation is associated with a change of HHI in the MSA level. The state population density is also relatively constant before and after the Riegle-Neal Act with a mean around 134 persons per square miles.

4.4 MAIN REGRESSION RESULTS

4.4.1 INTRASTATE BRANCHING AND INTERSTATE BANKING

To test the relation between intrastate branching, interstate banking, and bank risk, we estimate the following empirical specification using the sample period from 1984:Q1 to 1994:Q3.

$$Risk_{i,j,t-k+1,t} = \alpha + \beta_1 \cdot Intra_{j,t} + \beta_2 \cdot Inter_{j,t} + \beta_3 \cdot Controls_{i,j,t-k} + \gamma_i + \delta_t + \varepsilon_{i,j,t-k+1,t} \qquad (3)$$

where *Risk* is (inverse) bank risk as measured by *Ln Z-Score*, *Intra* is an indicator variable of intrastate branching deregulation, *Inter* is an indicator variable of interstate banking deregulation, *Controls* is the vector of bank control variables as explained in

Sub-Section 3.2, γ and δ represent bank and time (quarter) fixed effects respectively,[60] while ε denotes an error term. $i, j,$ and t are indexes for bank, state, and time respectively. The risk variables are measured over k quarters from time $t-k+1$ to t, while the control variables are measured at time $t-k$ to ensure that they are predetermined relative to the risk variables.[61] Meanwhile, the indicator variables of bank deregulation are measured at time t so that our coefficients of interest, β_1 and β_2, can be interpreted as the treatment effects of a generalized Difference-in-Differences (DID) estimation.[62] Since risk variables are likely correlated within a bank over time, we use cluster-robust standard errors (Rogers, 1993) at the bank level in the estimation.

Table 4.2, Panel A, presents our main results from the multivariate analysis. In all columns, except for column (1) and (2) when we put no control variable other than bank and time fixed effects, *Intra* is negative and statistically significant at the 1 percent level. This finding suggests that the intrastate branching deregulation increased banks' overall risk. Meanwhile, *Inter* is positive and statistically significant at the 1 percent level in all of the regression specifications. This finding shows that the interstate banking deregulation decreased banks' overall risk. In terms of the economic importance of our results, *Intra*'s coefficient is about -0.03, which means that the level of *Z-score* of banks in states allowing intrastate branching is lower by 2.96 percent than those in states prohibiting it, holding all other variables constant. *Inter*'s coefficient is about 0.20, which

[60] As one of the robustness checks, we control for state fixed effects instead of bank fixed effects and our main results are still robust.

[61] Several researchers argue that the simultaneity concern between a dependent variable and an endogenous independent variable can be mitigated by replacing the independent variable with its lagged value, for example see Gupta (2005), Duchin, Ozbas, and Sensoy (2010), and Buch, Koch, and Koetter (2013).

[62] Jayaratne and Strahan (1996) drop observations in year of deregulation in their DID specification. Our results are robust when we conduct this treatment.

suggests that the level of *Z-score* of banks in states allowing interstate banking is higher by 22.14 percent than those in states prohibiting it, holding all other variables constant.[63]

As the intrastate branching increased the market power of local banks, while the interstate banking deregulation decreased it (Chava, Oettl, Subramanian, Krisnamurthy, and Subramanian, 2013), our main results support the ***Competition-Stability Hypothesis***. However, the coefficient magnitudes suggest that the interstate banking impact on bank risk is much more material than the intrastate branching. Our findings are in line with the previous studies such as Rivard and Thomas (1997) and Goetz, Laeven, and Levine (2016) that find BHCs had lower risk following the interstate banking deregulation. However, their studies have focused only on BHCs, while our study cover all commercial banks, BHCs and nonBHCs, from small to large money center banks.

4.4.2 INTERSTATE BRANCHING

To test the relation between interstate branching and bank risk, we estimate the following empirical specification using the sample period post the Riegle-Neal Act from 1994:Q4 to 2013:Q4.

$$Risk_{i,j,t-k+1,t} = \alpha + \beta_1 \cdot RSI_{j,t} + \beta_2 \cdot Controls_{i,j,t-k} + \gamma_i + \delta_t + \varepsilon_{i,j,t-k+1,t} \qquad (4)$$

where *RSI* is the interstate branching restrictiveness index based on Rice and Strahan (2010). All control variables and standard errors adjustment are the same as in equation (3). Note that as *RSI* is not an indicator variable, and therefore, equation (4) is not a DID estimation.

[63] Halvorsen and Palmquist (1980) show that the coefficient of a dummy variable (β_j) in a semilogarithmic regression equation should be interpreted as the $100(\exp\{\beta_j\} - 1)$ percentage change in Y for a discrete change in the dummy from 0 to 1.

Table 4.2, Panel B, presents our results from the multivariate analysis. In all columns, we find positive coefficients on *RSI*. Except for column (1), the coefficients are statistically significant only at the 10 percent level. This result implies that the interstate branching deregulation (less restrictions on interstate branching) increased banks' overall risk. However, similar with intrastate branching, the impact of interstate branching on bank risk is much weaker compared to the interstate banking. In particular, the *RSI*'s coefficient magnitude is about 0.006, which means that the level of *Z-score* of banks in states having no restrictions on intrastate branching (RSI equals to 0) is lower by 2.4 percent than those in states having maximum restrictions (RSI equals to 4), holding all other variables constant. This finding is consistent with Dick (2006) that documents an increase in loan charge-offs following the interstate branching deregulation. However, Dick's paper does not consider the variation on each state's provision to defense from the nationwide branching expansion. Our paper is the first that considers this state provision variation using the interstate branching restrictiveness index based on Rice and Strahan (2010).

4.5 ENDOGENEITY

We are aware that there might be a reverse causality between bank risk and deregulation. For example, a state with relatively risky banks could have incentives to allow bank deregulation so that the banks can reduce their risk through diversification by opening new branches within the state, acquiring out-of-state banks, or opening out-of-state branches. Alternatively, a state might wait until its banks are strong enough financially before allowing a deregulation to mitigate possible bank distress caused by tougher competition post the deregulation. We address this concern by using the Instrumental Variable (IV) regression that can isolate the exogenous component of bank deregulation. Following Berger, Klapper, and Turk-Ariss (2009), we use an IV technique with a Generalized Method of Moments (GMM) estimator to mitigate a potential heteroscedasticity problem. Furthermore, consistent with our OLS models, we employ the clustered standard errors at the bank level for the IV estimation.

4.5.1 INSTRUMENTAL VARIABLE REGRESSION

We use deregulation variables of adjoining states as our instruments.[64] There is a large strand of literature on state policy diffusion related to federalism in the U.S., which contends that there is an interdependent regional effect on public policy making at the state level (e.g. Berry and Berry, 1990; Mooney, 2001; Shipan and Volden, 2008; Gillardi, 2010). In general, these studies show that a U.S. state tends to follow its adjoining states to adopt a law. There are at least two reasons through which a state may follow its adjoining states' policies for its own public policy making. First, adopting a public policy that has been adopted by adjoining states attenuates the political risk associated with the policy. If the policy fails, the state's politicians will not take the full blame for it and instead, they can blame on the systematic factors affecting states in the same region. Second, states in the same geographic region might compete for each other to attract new investments. Accordingly, a state will closely observe its adjoining states in terms of laws adoption to make sure that the state can compete with its adjoining states to

[64] For Alaska and Hawaii, we follow Berger and Sedunov (2016) to determine these states' adjoining states. Alaska's adjoining states are Hawaii, Oregon, Washington, and California. Meanwhile, the adjoining states for Hawaii are Alaska, Oregon, Washington, and California.

attract new investments.[65] Since our analysis is at the bank level for each state, we do not expect that the deregulation of adjoining states directly affects our dependent variable.

The IV regression results are reported in Table 4.3. Panel A shows the first and second stage IV regression estimates on the first subsample prior to the Riegle-Neal Act. Since there are two endogenous variables estimated in the second stage, *Intra* and *Inter*, we use two instruments on the first stage. The instrument for *Intra* is the average of *Intra* indicator variables from adjoining states, weighted by each of the adjoining state's area. Similarly, the instrument for *Inter* is the area-weighted-average of *Inter* indicator variables from adjoining states. Column (2) and (3) of Panel A show the *F-statistics* for each of our instrument in the first stage IV estimation, which are all statistically significant at the 1 percent level and far beyond 10, suggesting that our instruments have strong correlations with both of the deregulation variables.[66] We also compute the Kleibergen-Paap rk LM statistic for both instruments that rejects the null hypothesis at 1 percent level, suggesting that our IV regression is well identified. Moreover, the columns show that all of our instruments' coefficients are positive and statistically significant at 1 percent level, which is consistent with the state policy diffusion literature. In particular, our results show evidence that a state is more likely to allow intrastate branching or interstate banking activities if its adjoining states have already done so, holding all other else constant. Finally, column (4) shows the second stage estimation results of our IV regression. Both of the *Intra* and Inter *coefficients* from the IV regression have the

[65] For a more literature review on state policy diffusion, see for example, Mooney (2001).
[66] Staiger and Stock (1997) suggest that a problem of weak instruments is less likely if the F-statistics on the excluded instruments is greater than 10. As further robustness tests, we also check the Cragg-Donald Wald F statistics, Kleibergen-Paap Wald rk F statistics, Anderson-Rubin Wald statistics, and Stock-Wright LM S statistics. Almost all of these tests in models (1)-(7) reject the null hypothesis that the instruments are weak at the 5 percent level.

consistent sign and statistical significance with the OLS estimates that are reported in column (1), i.e. the OLS results from the model (9) of Panel A in Table 4.2.[67]

Panel B of Table 4.3 shows the IV regression results in the second subsample post-the Riegle-Neal Act. Similar with *Intra* and *Inter,* we instrument *RSI* with the area-weighted-average of *RSI* from adjoining states. Column (2) presents the estimation results from the first stage regression. Both of the *F* and Kleibergen-Paap rk LM statistics for the instrument are statistically significant at 1 percent level, which suggests that the instrument is relevant and the IV model is well-identified. Still consistent with the state policy diffusion literature, the coefficient estimate of the instrument is positive and statistically significant at 1 percent level, which suggests that a state is more likely to relax restrictions on interstate branching by out-of-state banks if its adjoining states have already done so, holding all other else constant. In column (3), we do not find significant evidence that interstate branching is associated with bank risk. This result is consistent with our finding from the OLS model.

4.5.2 CONTIGUOUS COUNTY MATCHING

Other potential source of endogeneity is the omitted variable bias. To address this concern, first, we control for state and bank-specific variables that can affect bank risk based on the previous literature, as we have discussed in subsection 4.3.4. Next, we run OLS regressions on contiguous county matching (CCM) samples, following Huang (2008). In particular, we run OLS regressions as specified in equation (3) and (4) only on

[67] The finding with larger coefficient estimates from the IV compared to the OLS regression is consistent with for example, Levitt (1996), Berger and Bouwman (2009), and Berger, El Ghoul, Guedhami, and Roman (2016).

banks that are located in contiguous counties separated by state borders.[68] As contiguous counties are more likely to have similar characteristics, we may expect that this strategy is able to address the bias from factors that we cannot observe to control (e.g. economic potentials or growth opportunities).

The results are shown in Panel C of Table 4.3. Pre-the Riegle-Neal Act, we find a consistent result with the OLS and IV results in which *Inter* is positive and statistically significant at the 1 percent level. The coefficient's magnitude is about 0.15, which is economically material. The coefficient for *Intra* is not statistically significant. Post-the Riegle-Neal Act, the coefficient estimate of *RSI* is also not statistically significant, consistent with the results of the previous endogeneity analyses.

Since the OLS results show negligible evidence that interstate branching affects bank risk, and no significant evidence of this relation using IV, as well as CCM sample analysis, we will focus the analyses on the rest of this paper only on the intrastate branching and interstate banking deregulation.

4.5.3 PLACEBO REGRESSION

Panel D of Table 4.3 shows the placebo (falsification) test on the impact of intrastate branching and interstate banking deregulation on bank risk. This analysis aims to test the internal validity of our research design, i.e. whether our main analysis as in equation (3) indeed captures the effect of intrastate branching and interstate banking deregulation on bank risk. We start with generating 500 random sets of Intrastate Branching and Interstate Banking deregulation years for each state using a uniform distribution. The random years generated for Intrastate Branching are between 1970 (the

[68] The county adjacency data are available at https://www.census.gov/geo/reference/county-adjacency.html.

earliest year of intrastate branching permitted) and 1999 (the latest year of intrastate branching permitted). We follow Kroszner and Strahan (1999) and Francis, Hasan, and Wang (2014) to use 1970 as the year of intrastate branching permitted if a state has permitted the deregulation before 1970. Meanwhile, the random years generated for Interstate Banking are between 1978 (the earliest year of interstate banking permitted) and 1997 (the latest year of interstate banking permitted). Then, we run 500 different OLS regressions as in equation (3), with standard errors that are clustered at the bank level using Intra and Inter that are generated using the random deregulation years. Finally, we calculate the mean of the Intra and Inter coefficient estimates from the 500 placebo regressions and test whether they are significantly different than zero. The results in Panel D of Table 4.3, show that none of the mean of the Intra and Inter coefficient estimates from the placebo regressions is statistically significant. This suggests that our main research design is less likely to suffer from a weak internal validity.

4.6 ROBUSTNESS CHECKS

4.6.1 ALTERNATIVE BANK RISK MEASURES

Firstly, we conduct robustness tests using several alternative risk measures in Panel A of Table 4.4. Column (1) shows the baseline result using *Ln Z-Score* as the risk measure. We find consistent results for *Inter* using all alternative risk measures. In particular, the interstate banking deregulation is associated with higher *Ln Sharpe*, lower *SDROE*, lower *SDROA*, higher capitalization (*EQTA*), lower loan concentration (*LPC*), and lower *NPL* ratio. Meanwhile, intrastate branching is associated with higher *SDROE*, higher *SDROA*, and lower capitalization *EQTA*. These results are consistent with our main findings.

4.6.2 OTHER ROBUSTNESS CHECKS

We continue our robustness tests using several alternative samples in Panel B of Table 4.4. In column (1), we run our main regression by excluding banks in South Dakota and Delaware. Previous bank deregulation studies often exclude South Dakota and Delaware from their samples because in the 1980s these states passed unique usury laws providing great incentives for the credit card industry. This resulted in both states having a significant presence of credit card banks in their banking systems (Jayaratne and Strahan, 1996; Black and Strahan, 2002; Beck, Levine, and Levkov, 2010; Subramanian and Yadav, 2012; Francis, Hasan, and Wang, 2014; Goetz, Laeven, and Levine, 2016). In column (2) to (3), we exclude very large banks that might be Too-Big-to-Fail (TBTF) using different threshold definitions, including the Dodd-Frank Act's definition (banks with total assets larger than $50 billion), as well as banks that are subject to the Supervisory Capital Assessment Program (SCAP) and Comprehensive Capital Analysis and Review (CCAR). Next, we run our main multivariate analysis using a block bootstrap technique in column (4), which aims to address a potential concern of inconsistent standard errors from the DID regression, as suggested by Bertrand, Duflo, and Mullainathan (2004).[69] To account for the possible serial correlation in the data, we use bank level blocks (clusters). Our results for these specifications are consistent with

[69] Following Bertrand, Duflo, and Mullainathan (2004), the bootstrap resampling process uses 400 repetitions.

the main findings. In particular, interstate banking is associated with higher *Ln Z-Score*, while intrastate branching is associated with lower *Ln Z-Score.*

We are aware that our results might be affected by the dynamics of the U.S. banks' entry and exit during our main sample period. In particular, it could be that after bank deregulation opens up the market, bad banks are acquired by good banks, which leaves the industry with relatively more stable banks. Stiroh and Strahan (2003) show that after intrastate branching and interstate banking deregulation, there is a substantial reallocation of market share toward better banks. We address this concern by running OLS regressions using a balanced panel of banks in column (5). Specifically, we run the regressions after excluding all banks that partially exist during our main sample period and, therefore, restrict the analysis to banks that are fully operational during the main sample period.[70] Next, in column (6) we run our main OLS analysis with two-way cluster standard errors at the bank and quarter levels to test whether there is a potential heteroscedasticity problem in smaller clusters that may affect our main results. Finally, in column (7), we conduct our analysis at the BHC level instead of bank level. The results on all of the specifications in column (5)-(7) are consistently showing that interstate banking is positively associated with *Ln Z-Score.* However, intrastate branching coefficient becomes statistically insignificant.

[70] In these regressions we rule out new entrant banks and banks that exit the industry during the sample period, which could be caused by M&A activities or bank defaults.

4.7 COMPETITION, DEREGULATION, AND BANK RISK

4.7.1 REGRESSION RESULTS BASED ON STATE POPULATION DENSITY

Bank deregulation that allows banks to expand their markets may enable them to gain lower-cost funds, increase investment opportunities, and promote productive efficiency due to takeover threats. The previous literature shows that banks might benefit from diversification as they expand their market geographically (e.g. Akhigbe and Whyte (2003), Deng and Elyasiani (2008), and Goetz, Laeven, and Levine (2016)). Statewide (intrastate) branching deregulation enables banks to expand their deposits base and diversify their loans portfolio within the state. Therefore, we may expect that this deregulation is more beneficial for states with relatively dense population. On the contrary, we may expect that interstate banking is more crucial for states where the population is sparse and banks have less opportunity to diversify geographically within the states. Table 4.5 shows the regression estimates based on state population density grouping. A state is defined as "sparsely populated" if its population density is below the 25th percentile. Meanwhile, if the state has population density between the 25th and 75th percentiles, we define it as a "fairly populated" state. Finally, the state is defined as "densely populated" if its population density is above the 75th percentile. The results confirm or prediction that intrastate branching is associated with higher *Ln Z-Score* for banks in densely populated states, but associated with lower *Ln Z-Score* for banks in fairly and sparsely populated states. Meanwhile, interstate banking is associated with higher *Ln Z-Score* for banks in sparsely populated and fairly populated states.

4.7.2 REGRESSION RESULTS BASED ON BANK SIZE

Table 4.6 reports regression estimates of the impact of Intrastate Branching and Interstate Banking deregulation on bank risk based on bank size. Following Berger and Bouwman (2013), small banks are defined as commercial banks having real GTA up to $1 billion, medium banks are those having real GTA between $1 billion and $3 billion, and large banks are those having real GTA greater than $3 billion. The results show that the positive impact of interstate banking on *Ln Z-Score* is driven by small banks. This finding is different than the previous literature that mainly attributes the positive impact of interstate banking on bank stability to large banks due to their ability to take advantage on interstate diversification. Meanwhile, intrastate branching has significantly positive impact on large banks, but negative on small and medium banks.

In Table 4.7, we conduct a further investigation by running regressions of *Ln Z-score* to intrastate branching and interstate banking using a subsample of small banks that stay to be unit banks and are not part of any BHC between 1984:Q1-1994:Q3. We would expect that these banks have less ability to benefit from the diversification channel. Therefore, if we observe any positive impact of intrastate branching and interstate banking on these banks, we might attribute specifically this to the Competition-Stability channel. The results on Panel A show statistically significant evidence on this. Furthermore, Panel B shows that the results in Panel A are driven by "strong" small unit banks, which suggest that these banks are forced to improve by the increase of competition due to geographic deregulations, especially the interstate banking.[71] On the flip side, Panel C shows that "weak" small unit banks become riskier post the

[71] "Weak" small unit banks are defined as small unit banks that will be listed on the FDIC list of failed banks during the sample period. "Strong" banks are defined as the other way around.

deregulation. These results might suggest that the increase in competition due to the geographic bank deregulation affects small banks in in two ways: the deregulation encourages the strong small banks to be better, but kills the weak small banks resulting in creative destruction as in Schumpeter (1942).

4.8 CONCLUSION

There has been a long-standing debate among economists, regulators, politicians, and policymakers about the impact of geographic deregulation on bank risk. Deregulation presents an opportunity for banks to diversify their assets and extend their depositor bases, and it increases competition level in local markets. The literature shows that an increase in either diversification or competition has an ambiguous impact on bank risk. Therefore, whether bank deregulation increases or reduces risk is still an open empirical question.

In this paper, we study two major geographic deregulations of banking activities in the 1970s and 1980s—intrastate branching and interstate banking deregulation. We find strong evidence that interstate banking deregulation is associated with lower bank risk, but no evidence that intrastate branching deregulation affects bank risk. These findings are robust to a variety of robustness checks, including endogeneity (reverse causality) and sample selection bias. Moreover, the data persistently suggest that the *Diversification-Stability Channel* dominates the *Competition-Stability Channel* as the mechanism by which deregulation reduces bank risk. We also document that the impact of deregulation on bank risk is stronger in the long term. Finally, though we find some evidence that the Riegle-Niel Act deregulation in interstate branching activities also lowers risk, the magnitude is negligible, suggesting that its impact is subsumed by interstate banking deregulation.

Table 4.1: Variable Definition and Summary Statistics

This table presents the definition of all variables analyzed and their respective summary statistics. **Panel A** presents the definition of all variables in the analysis. **Panel B** reports summary statistics for all U.S. commercial banks before the Riegle-Neal Act (1984:Q1-1994:Q3). **Panel C** reports summary statistics for all U.S. commercial banks after the Riegle-Neal Act (1994:Q4-2013:Q4). We use 1994:Q4 as the start of the latter sample period as the former U.S. President, Bill Clinton, enacted and signed the Riegle-Neal Act on September 29, 1994. All variables in dollar amounts are expressed in real terms using the 2010:Q4 implicit GDP price deflator. All financial ratios are winsorized at 1% level on top and bottom of the distribution.

Panel A: Variable Definition

Variable	Definition
Bank Risk Measures:	
Ln Z-Score	The main measure of bank risk calculated as $\ln(1+\lvert\min(Z\text{-}Score)\rvert+Z\text{-}Score)$. The *Z-Score* is calculated as $\left(\mu(ROA)+\mu\left(\frac{Equity}{GTA}\right)\right)/\sigma(ROA)$. A lower value indicates a higher financial risk. The mean (μ) and standard deviation (σ) are calculated over 12 quarters from time $t-11$ to time t. *Return on Assets* (ROA) is defined as the ratio of net income to *Gross Total Assets (GTA)*. *GTA* is defined as total assets + allowance for loan and lease losses + allocated transfer risk reserves.
Ln Sharpe	An alternative measure of bank risk calculated as $\ln(1+\lvert\min(Sharpe\ Ratio)\rvert+Sharpe\ Ratio)$. The *Sharpe Ratio* is defined as $\mu(ROE)/\sigma(ROE)$. ROE is defined as the ratio of net income to total equity. A lower value indicates a worse risk-adjusted return. The mean (μ) and standard deviation (σ) are calculated over 12 quarters from time $t-11$ to t.
SDROE	A measure of bank profit's volatility, defined as the standard deviation of *Return on Equity* (ROE). *ROE* is calculated as the ratio of net income to total equity. A higher value is associated with higher bank risk. This measure is calculated over 12 quarters from time $t-11$ to time t.
SDROA	A measure of bank profit's volatility, defined as the standard deviation of ROA. A higher value is associated with higher bank risk. This measure is calculated over 12 quarters from time $t-11$ to time t.
EQTA	A measure of bank capitalization that is calculated as *Total Equity/GTA*. This measure is averaged over 12 quarters from time $t-11$ to t.
LPC	A measure of bank loan portfolio concentration that is calculated as $\sum_{n=1}^{5} LS_{nit}^2$, following Demsetz and Strahan (1997) and Berger, Bouwman, Kick, and Schaeck (2016). This measure lies between 0 and 1, where higher number shows higher concentration (lower diversification) in a bank's loans portfolio. LS_{nit} is the ratio of loan category n of bank i at time t to total loans. There are five loan categories (n) included, i.e. commercial and industrial loans, personal loans, commercial real estate loans, residential real estate loans, and other loans. This measure is averaged over 12 quarters from time $t-11$ to t.
NPL/TL	A measure of credit risk defined as the mean of nonperforming loans (past due at least 90 days or in nonaccrual status) to total loans. A higher value indicates a riskier loan portfolio. This measure is averaged over 12 quarters from time $t-11$ to t.

(Continued)

Table 4.1: Variable Definition and Summary Statistics

Panel A: Variable Definition

Variable	Definition
Bank Deregulation:	
Intrastate Branching (Intra)	An indicator variable equals to 1 in a year when a state allows statewide branching via mergers and acquisitions and the years after; 0 otherwise. The timing of the intrastate branching is based on Amel (1993) and Kroszner and Strahan (1999).
Interstate Banking (Inter)	An indicator variable equals to 1 in a year when a state allows bank acquisition by out-of-state banks and the years after; 0 otherwise. The timing of the interstate banking is based on Amel (1993) and Kroszner and Strahan (1999).
Interstate Branching (RSI)	An index measuring the degree of interstate branching restriction by state that ranges from 0 (no restriction) to 4 (fully restricted), based on Rice and Strahan (2010). This index is a sum of indicator variables on *Minimum Age Restriction*, *De Novo Branching Restriction*, *Branch Acquisition Restriction*, and *Deposit Cap Restriction* that will be explained below. We update the data using the Profile of State-Chartered Banking (PSCB) and State Banking Laws. If there is any difference on interstate branching restriction between the PSCB and Rice and Strahan (2010), we follow Rice and Strahan.
Minimum Age Restriction	An indicator variable equals to 1 if a state imposes a minimum age of 3 or more years on target banks of interstate acquirers, and 0 otherwise, following Rice and Strahan (2010).
De Novo Branching Restriction	An indicator variable equals to 1 if a state does not permit de novo interstate branching, and 0 otherwise, following Rice and Strahan (2010).
Branch Acquisition Restriction	An indicator variable equals to 1 if a state does not permit the acquisition of individual branches or portions of banks by an out-of-state bank, and 0 otherwise, following Rice and Strahan (2010).
Deposit Cap Restriction	An indicator variable equals to 1 if a state imposes a deposit cap less than 30%, and 0 otherwise, following Rice and Strahan (2010).
Control Variables:	
Ln Gross Total Assets (GTA)	A measure of bank size calculated as the natural logarithm of *Gross Total Assets (GTA).*
Population Density	A measure of a state population density that is calculated as the state's total population (in 1,000 persons) divided by the state's area (in square miles).
Ln Housing Price Index	The log natural of Housing Price Index of each state. The index is available from the Federal Housing Finance Agency (FHFA)'s website. Following Klarner (2013), we divide the index by 100.
BHC	An indicator variable equals to 1 if the bank is part of a bank holding company, and 0 otherwise.
Listed	An indicator variable equals to 1 if the bank is listed on a stock exchange or is part of a Bank Holding Company that is listed on a stock exchange, and 0 otherwise.
Asset Diversification Ratio	A measure of diversification across different types of earning assets, calculated as $1-\left\lvert\frac{\text{Net loans-Other earning assets}}{\text{Total earning assets}}\right\rvert$, following Laeven and Levine (2007). This measure takes values between 0 and 1 with higher values indicating greater diversification.

(Continued)

Table 4.1: Variable Definition and Summary Statistics

Panel A: Variable Definition

Variable	Definition
Overhead Costs Ratio	A measure of bank overhead cost structure calculated as the ratio of overhead expenses to *GTA*.
Foreign Assets Ratio	A measure of bank internationalization defined as the ratio of foreign total assets to *GTA* of the bank, following Berger, El Ghoul, Guedhami, and Roman (2016); a larger value indicates a higher degree of internationalization and a ratio of 0 refers to purely domestic banks.
HHI of Deposits	The Herfindahl-Hirschman Index (HHI) of bank deposits, which measures the degree of concentration of commercial banks at the local market level. This measure is defined as the weighted average of HHI at MSA/NECMA/county level where each bank operates. The HHI at MSA/NECMA/county level is calculated as the sum of squared market share of deposits for all commercial banks in the MSA/NECMA/county.

Panel B: Summary Statistics Pre-the Riegle-Neal Act (1984:Q1-1994:Q3)

Variables	N	Mean	St. Dev	Skewness	P25	P50	P75
Bank Risk Measures:							
Ln Z-Score	303,207	3.003	0.873	-0.389	2.448	3.102	3.634
Z-Score	303,207	26.349	22.937	1.687	9.754	20.420	36.048
Ln Sharpe	303,212	1.356	0.611	0.085	0.914	1.357	1.784
Sharpe	303,212	2.928	3.053	1.601	0.741	2.130	4.203
SDROE (%)	303,212	13.196	23.624	3.879	3.094	5.445	11.369
SDROA(%)	303,207	0.840	1.017	2.865	0.270	0.473	0.941
EQTA (%)	303,207	8.621	2.634	1.863	6.944	8.080	9.682
LPC	303,099	0.310	0.092	1.961	0.249	0.282	0.340
NPL/TL (%)	303,099	2.278	2.032	1.621	0.856	1.643	3.023
Bank Deregulation:							
Intrastate Branching	303,207	0.776	0.417	-1.323	1	1	1
Interstate Banking	303,207	0.908	0.289	-2.818	1	1	1
Control Variables:							
Ln Gross Total Assets (Ln GTA)	303,207	11.512	1.101	1.831	10.749	11.290	11.959
Gross Total Assets (GTA), in billion $	303,207	0.441	4.301	34.629	0.047	0.080	0.156
Population Density (1,000 persons/sq. miles)	303,207	0.134	0.412	20.209	0.049	0.074	0.168
Ln Housing Price Index (Ln HPI)	303,207	0.271	0.203	1.499	0.144	0.236	0.356
Housing Price Index (HPI)	303,207	1.342	0.324	2.439	1.155	1.266	1.428
Bank Holding Company (BHC)	303,207	0.680	0.467	-0.771	0	1	1

(Continued)

Table 4.1: Variable Definition and Summary Statistics

Panel B: Summary Statistics Pre-the Riegle-Neal Act (1984:Q1-1994:Q3)

Variables	N	Mean	St. Dev	Skewness	P25	P50	P75
Listed	303,207	0.069	0.254	3.388	0	0	0
Assets Diversification Ratio (%)	303,207	28.329	21.743	1.037	11.881	23.310	39.728
Overhead Cost Ratio (%)	303,207	3.268	1.262	2.024	2.467	3.030	3.773
Foreign Assets Ratio (%)	303,207	0.075	0.594	8.098	0.000	0.000	0.000
HHI of Deposits	303,207	0.080	0.080	1.671	0.018	0.051	0.118

Panel C: Summary Statistics Post the Riegle-Neal Act (1994:Q4-2013:Q4)

Variables	N	Mean	St. Dev	Skewness	P25	P50	P75
Bank Risk Measures:							
Ln Z-Score	519,817	3.447	0.804	-0.575	2.971	3.532	4.018
Z-Score	519,817	39.676	29.898	1.284	17.700	32.384	53.765
Ln Sharpe	519,840	1.576	0.618	-0.243	1.175	1.608	2.013
Sharpe	519,840	4.040	3.503	1.203	1.485	3.240	5.730
SDROE (%)	519,840	6.770	12.859	6.600	2.096	3.481	6.317
SDROA (%)	519,817	0.590	0.798	4.018	0.205	0.338	0.618
EQTA (%)	519,829	10.214	3.161	2.018	8.165	9.431	11.360
LPC	519,411	0.320	0.094	1.918	0.256	0.293	0.353
NPL/TL (%)	519,363	1.167	1.303	2.772	0.360	0.772	1.482
Bank Deregulation:							
Interstate Branching (RS index)	519,817	2.456	1.470	-0.481	1	3	4
Control Variables:							
Ln Gross Total Assets (Ln GTA)	519,817	11.791	1.189	1.714	10.966	11.585	12.327
Gross Total Assets (GTA), in billion $	519,817	1.019	19.267	55.838	0.058	0.107	0.226
Population Density (1,000 persons/sq. miles)	519,817	0.134	0.275	24.111	0.052	0.083	0.189
Ln Housing Price Index (Ln HPI)	519,817	0.781	0.333	0.487	0.544	0.757	0.988
Housing Price Index (HPI)	519,817	2.315	0.863	1.700	1.722	2.131	2.686
Bank Holding Company	519,817	0.791	0.407	-1.432	1	1	1
Listed	519,817	0.119	0.323	2.358	0	0	0

(Continued)

Table 4.1: Variable Definition and Summary Statistics

Panel C: Summary Statistics Post the Riegle-Neal Act (1994:Q4-2013:Q4)

Variables	N	Mean	St. Dev	Skewness	P25	P50	P75
Assets Diversification Ratio (%)	519,817	54.577	26.340	-0.186	34.815	55.731	76.120
Overhead Cost Ratio (%)	519,817	3.212	1.282	2.710	2.476	2.990	3.626
Foreign Assets Ratio (%)	519,817	0.061	0.531	9.054	0.000	0.000	0.000
HHI of Deposits	519,817	0.085	0.075	1.803	0.023	0.069	0.121

Table 4.2: Main Regression Results

This table reports our main results using OLS regressions. **Panel A** reports the impact of Intrastate Branching and Interstate Banking deregulation on bank risk pre the Riegle-Neal Act from 1984:Q1-1994:Q3. **Panel B** reports the impact of Interstate Branching deregulation on bank risk post the Riegle-Neal Act from 1994:Q4-2013:Q4. The dependent variable for all panel is *Ln Z-Score,* an inverse measure of bank risk. A higher value indicates lower bank overall risk. The main explanatory variables in Panel A are *Intra* (an indicator variable equals to 1 in a year when a state allows statewide branching via mergers and acquisitions and the years after, and 0 otherwise) and *Inter* (an indicator variable equals to 1 in a year when a state allows bank acquisition by out-of-state banks and the years after, and 0 otherwise). The main explanatory variable in Panel B is *RSI*, an index measuring the degree of interstate branching restriction by state that ranges from 0 (no restriction) to 4 (fully restricted), based on Rice and Strahan (2010). All regressions include bank and time (quarter) fixed effects (FE). All right-hand-side control variables are lagged 12 quarters. All financial variables in dollar amounts are expressed in real terms using the 2010:Q4 implicit GDP price deflator. All financial ratios are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

Panel A: Intrastate Branching, Interstate Banking, and Bank Risk

	Dependent Variables: *Ln Z-Score*					
Independent Variables:	(1)	(2)	(3)	(4)	(5)	(6)
Intrastate Branching (Intra)	-0.003		-0.030***	-0.031***	-0.032***	-0.032***
	(-0.293)		(-2.810)	(-2.826)	(-2.982)	(-2.939)
Interstate Banking (Inter)		0.292***	0.201***	0.200***	0.200***	0.201***
		(19.355)	(13.513)	(13.437)	(13.476)	(13.566)
Ln Gross Total Assets (Ln GTA)			0.435*	0.391	0.347	0.350
			(1.719)	(1.543)	(1.351)	(1.369)
Ln GTA Squared			-0.034***	-0.032***	-0.031***	-0.031***
			(-3.056)	(-2.880)	(-2.735)	(-2.780)
Inflection point of *Ln GTA*			6.397	6.109	5.597	5.645
Population Density			0.115	0.106	0.126	0.132
			(0.227)	(0.209)	(0.251)	(0.263)
Ln Housing Price Index (Ln HPI)			-0.533***	-0.531***	-0.484***	-0.470***
			(-11.242)	(-11.171)	(-10.120)	(-9.850)
BHC				0.016	0.022	0.021
				(1.131)	(1.499)	(1.485)
Listed				-0.038**	-0.036**	-0.035**
				(-2.167)	(-2.013)	(-1.973)
Asset Diversification Ratio					0.002***	0.002***
					(13.681)	(13.624)
Overhead Cost Ratio					-0.018***	-0.018***
					(-5.000)	(-5.014)
Foreign Assets Ratio					0.035*	0.035*
					(1.943)	(1.940)
HHI of Deposits						1.307***
						(2.898)
HHI of Deposits-Squared						-3.404***
						(-2.623)
Inflection point of *HHI*						0.192

(Continued)

Table 4.2: Main Regression Results

Panel A: Intrastate Branching, Interstate Banking, and Bank Risk

	Dependent Variables: *Ln Z-Score*					
Independent Variables:	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.814***	2.589***	2.215	2.459*	2.789*	2.736*
	(353.420)	(193.582)	(1.535)	(1.700)	(1.903)	(1.870)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes	Yes	Yes
N	304,133	304,133	304,129	304,129	303,777	303,207
N-cluster	13,021	13,021	13,020	13,020	12,994	12,987
R-squared	0.701	0.705	0.715	0.716	0.717	0.717

Panel B: Interstate Branching and Bank Risk

	Dependent Variable: *Ln Z-Score*				
Independent Variables:	(1)	(2)	(3)	(4)	(5)
Interstate Branching (RSI)	0.003	0.007*	0.007*	0.006*	0.006*
	(0.792)	(1.855)	(1.827)	(1.654)	(1.669)
Ln Gross Total Assets (Ln GTA)		0.477***	0.485***	0.388***	0.380***
		(4.581)	(4.606)	(3.711)	(3.633)
Ln GTA Squared		-0.022***	-0.022***	-0.020***	-0.019***
		(-5.117)	(-5.173)	(-4.663)	(-4.602)
Inflection point of *Ln GTA*		10.841	11.023	9.700	10.000
Population Density		-0.073	-0.073	-0.074	-0.074
		(-1.247)	(-1.266)	(-1.287)	(-1.283)
Ln Housing Price Index (Ln HPI)		-0.272***	-0.274***	-0.295***	-0.299***
		(-5.310)	(-5.337)	(-5.817)	(-5.892)
BHC			-0.016	-0.009	-0.009
			(-0.988)	(-0.575)	(-0.574)
Listed			0.093***	0.092***	0.092***
			(2.705)	(2.746)	(2.750)
Asset Diversification Ratio				0.001***	0.001***
				(8.589)	(8.592)
Overhead Cost Ratio				-0.061***	-0.061***
				(-16.510)	(-16.376)
Foreign Assets Ratio				-0.013	-0.012
				(-0.740)	(-0.708)
HHI of Deposits					0.370
					(1.635)
HHI of Deposits-Squared					-1.142*
					(-1.827)
Inflection point of *HHI*					0.162
Constant	3.322***	0.817	0.791	1.759***	1.801***
	(190.031)	(1.278)	(1.226)	(2.713)	(2.773)
Bank FE	Yes	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes	Yes
N	520,669	520,667	520,667	520,110	519,817
N-cluster	11,983	11,983	11,983	11,974	11,964
R-squared	0.536	0.538	0.538	0.542	0.542

Table 4.3: Endogeneity

This table reports endogeneity checks of the impact of bank deregulation on bank risk. The dependent variable for all panel is *Ln Z-Score*, an inverse measure of bank risk. A higher value indicates lower bank overall risk. **Panel A** reports the Instrumental Variable (IV) regression estimates of the impact of Intrastate Branching and Interstate Banking deregulation on bank risk pre the Riegle-Neal Act from 1984:Q1-1994:Q3. The main explanatory variables in Panel A are *Intra* (an indicator variable equals to 1 in a year when a state allows statewide branching via mergers and acquisitions and the years after, and 0 otherwise) and *Inter* (an indicator variable equals to 1 in a year when a state allows bank acquisition by out-of-state banks and the years after, and 0 otherwise). The instrument variables in Panel A are *Intrastate Branching* and *Interstate Banking* indicators *of Adjoining States*, weighted averaged by the adjoining states' areas. **Panel B** reports the IV regression estimates of the impact of Interstate Branching deregulation on bank risk post the Riegle-Neal Act from 1994:Q4-2013:Q4. The main explanatory variable in Panel B is *Interstate Branching Index* (RSI), which measures the degree of interstate branching restriction by state that ranges from 0 (no restriction) to 4 (fully restricted), based on Rice and Strahan (2010). The instrument variable in Panel B is *Interstate Branching Index (RSI) of Adjoining States*, weighted averaged by the adjoining states' areas. **Panel C** presents the OLS regression estimates of banks that are headquartered in contiguous counties separated by state borders, closely follow Huang (2008). Column 1 shows the results for the first sub-sample period before the Riegle-Neal Act (1984:Q1-1994:Q3), and Column 2 shows the sub-sample period afterward (1994:Q4-2013:Q4). **Panel D** shows the Placebo regression result of the impact of Intrastate Branching and Interstate Banking on bank risk from 1984:Q1-1994:Q3. The procedures of the placebo test are as follow. First, we generate 500 random sets of Intrastate Branching and Interstate Banking deregulation years for each U.S. state using a uniform distribution. The random years generated for Intrastate Branching lies between 1970 (the earliest year of intrastate branching permitted) and 1999 (the latest year of intrastate branching permitted). We follow Kroszner and Strahan (1999) and Francis, Hasan, and Wang (2014) to use 1970 as the year of intrastate branching permitted if a state has permitted the deregulation before 1970. The random years generated for Interstate Banking lies between 1978 (the earliest year of interstate banking permitted) and 1997 (the latest year of interstate banking permitted). Then, we run 500 different OLS regressions using Intrastate Branching and Interstate Banking indicators that are generated using the random deregulation years. Finally, we average the coefficient estimates for Intrastate Branching and Interstate Banking and test whether they are significantly different than zero using t-tests. The average coefficient estimates, t-statistics from the t-tests, as well as the average number of observations, number of clusters, and R-squared across are shown in the table. All regressions include bank and time (quarter) fixed effects (FE). All right-hand-side control variables are lagged 12 quarters. Nonfinancial controls include *Population Density, Ln HPI, BHC, Listed, HHI*, and *squared HHI*. Financial controls include *Ln GTA, Ln GTA squared, Asset Diversification Ratio, Overhead Cost Ratio,* and *Foreign Assets Ratio.* All financial variables in dollar amounts are expressed in real terms using the 2010:Q4 implicit GDP price deflator. All financial ratios are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

(Continued)

Table 4.3: Endogeneity

Panel A: IV Regression—Intrastate Branching, Interstate Banking, and Bank Risk

Dependent Variables:	*Ln Z-Score*	*Intrastate Branching*	*Interstate Banking*	*Ln Z-Score*
	OLS (Baseline)	IV GMM 1st stage		IV GMM 2nd stage
Independent Variables:	(1)	(2)	(3)	(4)
Intrastate Branching (Intra)	-0.032***			-0.276***
	(-2.939)			(-5.178)
Interstate Banking (Inter)	0.201***			0.653***
	(13.566)			(5.797)
Intrastate Branching of Adjoining States		0.017***	0.183***	
		(2.678)	(22.17)	
Interstate Banking of Adjoining States		0.429***	0.0480***	
		(34.40)	(6.317)	
Nonfinancial controls	Yes	Yes	Yes	Yes
Financial controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes
N	303,207	302,905	302,905	302,905
N-cluster	12,987	12,685	12,685	12,685
R-squared (centered)	0.111	0.375	0.199	0.061
F-statistic of excluded instruments		670.25***	263.36***	
Kleibergen-Paap rk LM Statistics		489.97***		

(Continued)

Table 4.3: Endogeneity

Panel B: IV Regression—Interstate Branching and Bank Risk

Dependent Variables:	*Ln Z-Score*	*Interstate Branching (RSI)*	*Ln Z-Score*
	OLS (Baseline)	IV GMM 1st stage	IV GMM 2nd stage
Independent Variables:	(1)	(2)	(3)
Interstate Branching (RSI)	0.006*		-0.0323
	(1.669)		(-1.271)
Interstate Branching (RSI) of Adjoining States		0.276***	
		(26.18)	
Nonfinancial controls	Yes	Yes	Yes
Financial controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes
N	519,817	509,276	509,276
N-cluster	11,964	11,581	11,581
R-squared (centered)	0.116	0.474	0.114
F-statistic of excluded instruments		685.25***	
Kleibergen-Paap rk LM Statistics		701.04***	

(Continued)

Table 4.3: Endogeneity

Panel C: Contiguous County Matching

	Dependent Variable: *Ln Z-Score*	
Sub-sample Period:	Pre the Riegle-Neal Act (1984:Q1-1994:Q3)	Post the Riegle-Neal Act 1994:Q4-2013:Q4
Independent Variables:	(1)	(2)
Intrastate Branching (Intra)	0.011	
	(0.602)	
Interstate Banking (Inter)	0.148***	
	(6.277)	
Interstate Branching (RSI)		-0.002
		(-0.266)
Nonfinancial controls	Yes	Yes
Financial controls	Yes	Yes
Bank FE	Yes	Yes
Time (Quarter) FE	Yes	Yes
N	112,662	191,305
N-cluster	4,678	4,534
R-squared	0.688	0.542

Panel D: Placebo Regressions

	The Average Regression Coefficients of *Ln Z-Score on:*
Independent Variables:	(1)
Placebo Intrastate Branching (Intra)	0.006
	(1.488)
Placebo Interstate Banking (Inter)	-0.005
	(-1.437)
Nonfinancial controls	Yes
Financial controls	Yes
Bank FE	Yes
Time (Quarter) FE	Yes
Average N	303,207
Average N-cluster	12,987
Average R-squared	0.716

Table 4.4: Robustness Checks

This table reports robustness checks of the impact of Intrastate Branching and Interstate Banking deregulation on bank risk between 1984:Q1-1994:Q3. **Panel A** reports robustness checks using alternative risk measures as follows. Column 1 (baseline) uses *Ln Z-Score* as the dependent variable. A higher value indicates lower bank overall risk. Column 2 uses *Ln Sharpe.* A higher value indicates a better risk-adjusted return. Column 3 uses the standard deviation of Return on Equity (*SDROE*). A lower value indicates lower bank risk. Column 4 uses the standard deviation of Return on Assets (*SDROA*). A lower value indicates lower bank risk. Column 5 uses the mean of Equity to GTA ratio (*EQTA*). A higher value indicates lower bank risk. Column 6 uses the mean of Loan Portfolio Concentration measure (*LPC*). This measure lies between 0 and 1, where lower number shows less concentration in a bank's loans portfolio. Column 7 uses the mean of Non-Performing Loans/Total Loans ratio (*NPL/TL*), which measures a bank's exposure to credit risk. All dependent variables are calculated over 12 quarters from time $t - 11$ to t. **Panel B** shows other robustness checks as follows. Column 1 reports the OLS regression estimate that excludes all banks located in South Dakota and Delaware as these states have special laws on credit card banking. Column 2 excludes too-big-to-fail (TBTF) banks that are defined as all banks with real GTA above $50 billion, consistent with the Dodd-Frank Act Wall Street Reform and Consumer Protection Act of 2010 definition of systemically-important banks. Similar to column 2, in column 3 we exclude TBTF banks with alternative definition, i.e. 19 largest banks. We refer this definition to the U.S. government actions in 2009 that required 19 largest banks to conduct stress tests. These banks were promised of government assistance if they failed to increase capital on their own during the crisis. In column 4, we present the OLS regression estimate using the block bootstrap resampling technique, following Bertrand, Duflo, and Mullainathan (2004). In column 5, we present the OLS regression estimate that includes all banks that exist from the beginning until the end of the sample period, resulting in a balanced panel subsample. Column 6 reports the OLS regression estimates in which the standard errors are clustered two-way at the bank and quarter level. Finally, in column 7 we report the OLS regression estimate if we aggregate banks at the BHC level instead of bank level. All right-hand-side control variables are lagged 12 quarters. Nonfinancial controls include *Population Density, Ln HPI, BHC, Listed, HHI*, and *squared HHI*. Financial controls include *Ln GTA, Ln GTA squared, Asset Diversification Ratio, Overhead Cost Ratio,* and *Foreign Assets Ratio.* All regressions include bank and time (quarter) fixed effects (FE). All financial variables in dollar amounts are expressed in real terms using the 2010:Q4 implicit GDP price deflator. All financial ratios are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level unless stated otherwise. Numbers in parentheses are t-statistics.

Panel A: Alternative Risk Measures

Dependent Variables:	*Ln Z-Score* (Baseline)	*Ln Sharpe*	*SDROE*	*SDROA*	*EQTA(%)*	*LPC(%)*	*NPL/TL(%)*
Independent Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intrastate Branching (Intra)	-0.032***	-0.009	2.366***	0.096***	-0.074***	0.001	0.023
	(-2.939)	(-1.139)	(7.834)	(7.387)	(-3.871)	(1.475)	(0.899)
Interstate Banking (Inter)	0.201***	0.126***	-1.863***	-0.122***	0.223***	-0.004***	-0.521***
	(13.566)	(12.090)	(-4.407)	(-6.398)	(7.905)	(-3.716)	(-13.168)

(Continued)

Table 4.4: Robustness Checks

Panel A: Alternative Risk Measures

Dependent Variables:	*Ln Z-Score* (Baseline)	*Ln Sharpe*	*SDROE*	*SDROA*	*EQTA(%)*	*LPC(%)*	*NPL/TL(%)*
Independent Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nonfinancial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	303,207	303,212	303,212	303,207	303,207	303,099	303,099
N-cluster	12,987	12,987	12,987	12,987	12,987	12,980	12,980
R-squared	0.717	0.712	0.667	0.661	0.899	0.905	0.739

Panel B: Other Robustness Checks

	Dependent Variable: *Ln Z-Score*						
	Exclude Banks in South Dakota and Delaware	Exclude TBTF Banks (GTA > $50 billion)	Exclude TBTF Banks (19 largest banks each quarter)	Bootstrap	Balanced Panel	Two-Way Cluster	BHC Level
Independent Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intrastate Branching (Intra)	-0.031***	-0.032***	-0.031***	-0.032***	-0.014	-0.032	-0.009
	(-2.864)	(-2.913)	(-2.895)	(-3.052)	(-1.137)	(-1.287)	(-0.687)
Interstate Banking (Inter)	0.203***	0.202***	0.202***	0.201***	0.214***	0.201***	0.202***
	(13.356)	(13.586)	(13.602)	(13.833)	(13.734)	(6.938)	(11.683)
Nonfinancial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	299,409	302,885	302,637	303,207	240,845	302,905	194,750
N-cluster (Bank or BHC)	12,824	12,978	12,972	12,987	8,250	12,685	10,215
N-cluster (Quarter)						31	
R-squared	0.717	0.717	0.717	0.717	0.692	0.717	0.767

Table 4.5: Regression Results based on State Population Density Grouping

This table reports regression estimates of the impact of Intrastate Branching and Interstate Banking deregulation on bank risk between 1984:Q1-1994:Q3 based on state population density grouping. A state is defined as "sparsely populated" if its population density is below the 25th percentile. Meanwhile, if the state has population density between the 25th and 75th percentiles, we define it as a "fairly populated" state. Finally, the state is defined as "densely populated" if its population density is above the 75th percentile. The dependent variable for all panel is *Ln Z-Score*, an inverse measure of bank risk. A higher value indicates lower bank overall risk All regressions include bank and time (quarter) fixed effects (FE). All right-hand-side control variables are lagged 12 quarters. Nonfinancial controls include *Population Density, Ln HPI, BHC, Listed, HHI*, and *squared HHI*. Financial controls include *Ln GTA, Ln GTA squared, Asset Diversification Ratio, Overhead Cost Ratio,* and *Foreign Assets Ratio.* All financial variables in dollar amounts are expressed in real terms using the 2010:Q4 implicit GDP price deflator. All financial ratios are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

	Dependent Variable: *Ln Z-Score*			
	Baseline	Sparsely Populated States	Fairly Populated States	Densely Populated States
Independent Variables:	(1)	(2)	(3)	(4)
Intrastate Branching (Intra)	-0.032***	-0.183***	-0.052***	0.096***
	(-2.939)	(-7.298)	(-3.825)	(3.875)
Interstate Banking (Inter)	0.201***	0.047**	0.191***	0.119
	(13.566)	(2.269)	(7.842)	(0.908)
Nonfinancial controls	Yes	Yes	Yes	Yes
Financial controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes
N	303,207	64,207	158,455	80,545
N-cluster	12,987	3096	6950	3404
R-squared	0.717	0.723	0.738	0.684

Table 4.6: Regression Results based on Bank Size Grouping

This table reports regression estimates of the impact of Intrastate Branching and Interstate Banking deregulation on bank risk between 1984:Q1-1994:Q3 based on bank size. Following Berger and Bouwman (2013), small banks are defined as commercial banks having real GTA up to $1 billion, medium banks are those having real GTA between $1 billion and $3 billion, and large banks are those having real GTA greater than $3 billion. The dependent variable for all panel is *Ln Z-Score*, an inverse measure of bank risk. A higher value indicates lower bank overall risk. All regressions include bank and time (quarter) fixed effects (FE). All right-hand-side control variables are lagged 12 quarters. Nonfinancial controls include *Population Density*, *Ln HPI*, *BHC*, *Listed*, *HHI*, and *squared HHI*. Financial controls include *Ln GTA*, *Ln GTA squared*, *Asset Diversification Ratio*, *Overhead Cost Ratio*, and *Foreign Assets Ratio.* All financial variables in dollar amounts are expressed in real terms using the 2010:Q4 implicit GDP price deflator. All financial ratios are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

	Dependent Variable: *Ln Z-Score*			
	Baseline	Small Banks	Medium Banks	Large Banks
Independent Variables:	(1)	(2)	(3)	(4)
Intrastate Branching (Intra)	-0.032***	-0.045***	-0.323***	0.261**
	(-2.939)	(-4.172)	(-2.978)	(2.152)
Interstate Banking (Inter)	0.201***	0.190***	-0.047	0.083
	(13.566)	(12.901)	(-0.335)	(0.500)
Nonfinancial controls	Yes	Yes	Yes	Yes
Financial controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes
N	303,207	288,515	7,842	6,850
N-cluster	12,987	12,521	533	324
R-squared	0.717	0.728	0.717	0.669

Table 4.7: The Competition Channel—Regression Results on Small Unit Banks that Are Not Part of BHC

Panel A reports regression estimates of the impact of Intrastate Branching and Interstate Banking deregulation on bank risk using a sample of small banks that stay to be unit banks between 1984:Q1-1994:Q3 and are not part of any BHC. **Panel B** reports similar regression estimates as Panel A, but for "strong" small unit banks that are not part of any BHC. **Panel C** reports similar results for "weak" small unit banks that are not part of any BHC. "Weak" small unit banks are defined as small unit banks that will be listed on the FDIC list of failed banks. The dependent variable for column 1 and 2 is *Ln Z-Score*, an inverse measure of bank risk. A higher value indicates lower bank overall risk. Meanwhile, the dependent variables in the next four columns are mean Nonperforming loans ratio (*NPL/TL*), mean of Return on Assets (*ROA*), standard deviation of ROA (*σ(ROA)*), and mean of Equity/GTA ratio (*EQTA*) respectively. To be consistent with the *Ln Z-Score*, all of these alternative risk measures are calculated over 12 quarters. Higher values of NPL/TL or standard deviation of ROA indicate higher bank risk. Higher values of ROA and EQTA indicate lower bank risk. All regressions include bank and time (quarter) fixed effects (FE). All right-hand-side control variables are lagged 12 quarters. Nonfinancial controls include Population Density, Ln HPI, BHC, Listed, HHI, and squared HHI. Financial controls include Ln GTA, Ln GTA squared, Asset Diversification Ratio, Overhead Cost Ratio, and Foreign Assets Ratio. All financial variables in dollar amounts are expressed in real terms using the 2010:Q4 implicit GDP price deflator. All financial ratios are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

Panel A: All Small Unit Banks that Are Not Part of BHC

	All Small Banks (Baseline)	Small Unit Banks and Not part of BHC				
Dependent Variables:	*Ln Z-Score*	*Ln Z-Score*	*NPL/TL(%)*	*ROA(%)*	*σ(ROA)*	*EQTA(%)*
Independent Variables:	(1)	(2)	(3)	(4)	(5)	(6)
Intrastate Branching (Intra)	-0.045***	-0.016	-0.100	-0.095***	0.069	0.088
	(-4.172)	(-0.567)	(-1.128)	(-2.933)	(1.576)	(1.401)
Interstate Banking (Inter)	0.190***	0.123**	-0.544***	0.019	-0.104	0.404***
	(12.901)	(2.861)	(-3.514)	(0.391)	(-1.567)	(3.759)
Nonfinancial controls	Yes	Yes	Yes	Yes	Yes	Yes
Financial controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes	Yes	Yes
N	288,515	29,356	29,345	29,356	29,356	29,356
N-cluster	12,521	1738	1736	1738	1738	1738
R-squared	0.728	0.836	0.800	0.809	0.767	0.946

(Continued)

Panel B: "Strong" Small Unit Banks that Are Not Part of BHC

	All Small Banks (Baseline)	"Strong" Small Unit Banks and Not part of BHC				
Dependent Variables:	*Ln Z-Score*	*Ln Z-Score*	*NPL/TL(%)*	*ROA(%)*	$\sigma(ROA)$	*EQTA(%)*
Independent Variables:	(1)	(2)	(3)	(4)	(5)	(6)
Intrastate Branching (Intra)	-0.045***	-0.010	-0.178*	-0.084**	0.073*	0.149**
	(-4.172)	(-0.318)	(-1.945)	(-2.541)	(1.740)	(2.353)
Interstate Banking (Inter)	0.190***	0.128***	-0.592***	0.016	-0.110*	0.419***
	(12.901)	(2.979)	(-3.857)	(0.324)	(-1.660)	(3.905)
Nonfinancial controls	Yes	Yes	Yes	Yes	Yes	Yes
Financial controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes	Yes	Yes
N	288,515	27,503	27,492	27,503	27,503	27,503
N-cluster	12,521	1510	1508	1510	1510	1510
R-squared	0.728	0.819	0.785	0.765	0.728	0.951

Panel C: “Weak” Small Unit Banks that Are Not Part of BHC

	All Small Banks (Baseline)	“Weak” Small Unit Banks and Not part of BHC				
Dependent Variables:	*Ln Z-Score*	*Ln Z-Score*	*NPL/TL(%)*	*ROA(%)*	$\sigma(ROA)$	*EQTA(%)*
Independent Variables:	(1)	(2)	(3)	(4)	(5)	(6)
Intrastate Branching (Intra)	-0.045***	-0.043	1.023***	-0.175	-0.182	-0.642**
	(-4.172)	(-0.388)	(3.144)	(-1.113)	(-0.488)	(-2.189)
Interstate Banking (Inter)	0.190***	-0.260**	1.839**	0.062	0.582	-0.910
	(12.901)	(-2.487)	(2.320)	(0.233)	(1.436)	(-1.635)
Nonfinancial controls	Yes	Yes	Yes	Yes	Yes	Yes
Financial controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time (Quarter) FE	Yes	Yes	Yes	Yes	Yes	Yes
N	288,515	1,853	1,853	1,853	1,853	1,853
N-cluster	12,521	228	228	228	228	228
R-squared	0.728	0.896	0.880	0.868	0.793	0.930

CHAPTER 5

CONCLUSION

This dissertation consists of three essays that contribute to the literature of bank loan specialness, deposit insurance, and deregulation. The first essay provides empirical evidence of the certification value of bank loans from the U.S. market in the last two decades, which has experienced both market crisis and banking crisis. Using a novel dataset that merges 11,635 loan deals from the LPC Dealscan database and form 8-Ks from the SEC EDGAR between 1994-2014, I find that on average, only about 31% of bank loans are announced by firms. Among those loans announced, about 60% are cleanly announced and 40% are announced together with other events. Next, I find statistically and economically significant three-days Cumulative Abnormal Stock Return (CAR) following a loan announcement, which on average about +39 b.p., in line with the theory of bank loan specialness. The positive CARs are driven mainly by bank-dependent firms, which have never issued public bonds. Meanwhile, as a comparison, I show that three-days CARs following public bond announcements by firms in the sample are negative and statistically significant. Then, using the enactment of Sarbanes-Oxley Act of 2002 (SOX) and the SEC Rule ##33-8400 of 2004 as exogenous shocks to loan announcements by firms, I show significant evidence of sample selection bias in the loan announcements sample, which likely confounds the findings from the previous literature.

Being the first study that corrects the sample selection bias, using the Heckman selection method, I find that a loan is more likely to be announced during a market crisis, relative to normal times, but not during a banking crisis, consistent with the asymmetric information hypothesis. Moreover, a loan is more likely to be announced by small firms, firms with lower EBITDA, and when the loan has more financial covenants, is a revolver loan, has a longer maturity, secured, as well as when the firm has a previous relationship with the same lender in the past 5 years. Then, I find that the CARs are significantly higher during a banking crisis, compared to normal times, but not in a market crisis, in line with both the asymmetric information hypothesis and the institutional memory hypothesis. In terms of loan, firm, and lender characteristics, CAR is statistically higher for a loan announced by a bank-dependent firm, and for a loan that has more financial covenants, and is a revolver. I also find some evidence CAR is statistically higher for a loan that has a longer maturity as well as a loan made by the same lender that has lent the firm in the past 5 years. Finally, I find strong evidence that CAR is negatively associated with the market share of nonbank lenders, which aligns with the competition hypothesis that explains why CARs following loan announcements shown by the recent literature, including this paper, is not as high as the earlier studies have shown.

The second essay provides empirical evidence on how deposit insurance affects bank risk-taking and how this relation works on banks with different types of ownership, by using a unique natural experiment data from Indonesia from 2002:Q1-2011:Q4. I find a significant positive relation between explicit Deposit Insurance (DI) coverage and bank risk-taking, consistent with the moral hazard hypothesis. More specifically, controlling for various bank-specific and macroeconomic variables, as well as bank regulations, I find that Indonesian banks' *Z-score*, an inverse measure of bank risk taking, increases on average about 18% when the government switched from the blanket guarantee era to the limited guarantee era administered by the IDIC. In terms of mechanisms in which explicit DI coverage influences bank risk taking, I find that a lower explicit DI coverage is associated with lower bank profitability, lower standard deviation of profitability, and higher capitalization. Furthermore, I find some evidence that the relation is non-monotonic at the low level of explicit DI coverage, in line with the safety net hypothesis. This finding suggests that there is an optimum range of explicit DI coverage that sufficiently protects the depositors while curbing the banks' moral hazard problem. Finally, I find significant evidence that the impact of explicit DI coverage on bank risk is different across different kinds of ultimate owners. In particular, family banks and politically connected banks are those that are most affected when the government switched from the blanket guarantee era to the limited guarantee era, suggesting that the moral hazard problem in these banks are more prominent compared to foreign banks and nonpolitically connected banks.

The third essay (co-authored with Allen N. Berger, Sadok El Ghoul, and Omrane Guedhami) studies all three types of geographic deregulation in last three decades in the U.S. banking industry—intrastate branching, interstate banking, and interstate branching. These deregulations provide unique empirical settings to test the impact of competition and diversification on bank risk. We find statistically and economically significant evidence that on average, interstate banking deregulation is associated with about 22% increase in *Z-score*, an inverse indicator of overall bank risk. On the contrary, we find some evidence that intrastate branching is associated with a decrease in *Z-score* about

3%. Meanwhile, we find no evidence that interstate branching affects bank risk. These findings are robust to a variety of sensitivity checks, including those for endogeneity and sample selection bias, as well as alternative risk measures. Different than most of the previous studies that focus on large banks and Bank Holding Companies, our findings show that the favorable impact of interstate banking deregulation on bank risk are driven by small banks, which had opposed the deregulation with the fear that an increase in competition from large banks could reduce their survival probability. Meanwhile, intrastate branching is associated with higher risk for small and medium banks, but lower risk for large banks. These findings suggest that the competition-stability channel dominates for small and medium banks, while the diversification-stability channel dominates for large banks.

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