NAOAKI MINAMIHASHI

Credit Crunch Caused by Bank Failures and Self-Selection Behavior in Lending Markets

This study investigates how bank failures affect the real economy from the lenders' perspective. Using experimental settings of unique bank failures in Japan, this paper identifies the credit crunch effect by bank failures. The main findings are the following. First, bank failures decrease the investments of the client firms by approximately 30%. Second, the high investment growth/level firms deal with unhealthy banks. These choices generate a self-selection bias of 30–80%. Third, there is no evidence that bank-failure shock is related to the firms' accessibility to other financial sources.

JEL codes: E22, G21, G33
Keywords: bank failures, investment, credit crunch, self-selection, treatment effects.

How do bank failures cause or amplify recessions? When commercial banks go bankrupt, the depositors lose their deposits, the stock and debt holders of the bank lose their wealth, the client firms lose the relationships with their banks, and finally they fall into financially troubled conditions. As a result, these stakeholders' business activities stagnate, and this stagnation affects nonstakeholders of failed banks on many levels. Therefore, bank failures can ultimately affect the real economy. If so, banks should be protected.

To avoid these worst-case scenarios, governments and central banks have continuously attempted to prevent bank failures. They use substantial amounts of taxpayer money to rescue the troubled banks and justify their deeds using the above logic. However, is the government's or central bank's justification really legitimate? Is

This paper has benefited from the continuous advice, encouragement, and overall guidance of Simon Gilchrist and Marc Rysman. I acknowledge valuable suggestions from an anonymous referee. I am indebted to Francois Gourio, Hidehiko Ichimura, Jordi Jaumandreu, Joshua Lustig, Daniele Paserman, and Hirofumi Uchida for discussions that generated great improvements. I am also grateful to Fumio Akiyoshi, Saori Chiba, Nakcheon Choi, Fumio Hayashi, Chun-Yu Ho, Toru Kitagawa, Lori Lubeski, Tatsushi Oka, Konomi Tonogi, Vladimir Yankov, and the participants of Boston University Empirical Micro/Macro Workshop, Far Eastern Meeting of Econometric Society and Japanese Economic Association Meeting. I acknowledge funding of BU IED. I take full responsibility for any remaining errors.

Naoaki Minamihashi *is a PhD Candidate, Boston University, Department of Economics* (*E-mail*: naoaki@bu.edu).

Received October 26, 2009; and accepted in revised form July 6, 2010.

Journal of Money, Credit and Banking, Vol. 43, No. 1 (February 2011)

there any empirical evidence to support the concrete mechanisms of the breakdown? Some economists deny the negative effects of bank failures. They believe that the deposit insurance will protect the depositors, even though the amount is limited and the restoration process takes time. Also, other banks and other financial means will provide enough funds to the failed banks' clients in lending markets. Therefore, the bank failures do not strongly affect the real economy, and they are of little concern. The people who deny the negative effects question the policies that waste huge amounts of money to prevent bank failures, because we do not have the facts on how bank failures affect the real economy. Considering this controversial view, we need to delineate the mechanism of how bank failures cause or amplify recessions and which bank-failure shocks truly impact the economy.

In the past literature, Bernanke (1983), using macro data on the Great Depression, examined the bank-failure shocks on real economy and showed that the bank failures reduced U.S. production. However, Bernanke's results were criticized on the grounds that the recession itself just generates the bank failures and it is impossible to determine whether bank failures cause recessions or not. In response to this, Peek and Rosengren (2000) clarified that loan supply affects the real economy by investigating the shock of an exogenous banking crisis in Japan on the U.S. economy. Calomiris and Mason (2003), using an instrumental variables method, also showed the causality that the reduction of bank lending associated with bank failures decreases household income. More recently, Ashcraft (2005) found that bank failures cause recession independent of their economic status, using a natural experiment that banks in good health went bankrupt from chain bankruptcy. These papers confirmed that bank failures amplify recessions, but how bank failures amplify recessions is still an open question. Ashcraft (2005) predicted and explained the mechanism with three paths. First, the depositors, debt holders, and stock holders lose their wealth, or their liquidity, by bank failures. Second, the client firms cannot borrow from failed banks and fall into a credit crunch. This stagnates client firms' activity. Third, if other financial institutions carry the failed banks' debt, those banks easily go bankrupt or reduce lending to their client firms. These three direct shocks involve other unrelated entities, and finally they amplify (or even cause) the recession.

Even though the topic is of great importance, the empirical analyses of the mechanism how bank failures affect the real economy are few. This is mainly because the data that match failed banks with their depositors, debt holders, and client firms are difficult to obtain. Also, there exists an identification problem: it is difficult to identify the individual shocks because the three bank-failure shocks come simultaneously, involving unrelated entities. Many examples of bank failures in the previous literature were on small or regional banks, because governments frequently prevent large bank failures by the "too big to fail" policy. Therefore, most of the depositors and client firms were concentrated in a specific area. In this case, the three shocks affect each other because stakeholders concentrate in the small area and we cannot distinguish which shock truly affects the real economy and how much it does. These two problems make it difficult to analyze the mechanism of bank failures' shock.

This paper has two key features. First, it investigates how bank failures affect the real economy from the lenders' perspective.[1] This study identifies the credit crunch effect of bank failures on their client firms by analyzing the investment behavior of firms that lost their banks.[2] The key identification strategy is to use unique bank failures in Japan in the late 1990s.[3] The Japanese bank failures were suitable to estimate the shock. First, the banks were nationalized for nearly 2 years and the government restricted new loans. Second, the bank-failure shock was not concentrated in a specific area because the failed banks raised money not by deposits but by issuing bonds. Third, the Japanese accounting system provides us with precise loan quantity data that can link failed banks to their clients. Fourth, the government protected all of the debts and deposits. Under these settings, my paper aims to separate the direct shock in the loan markets from other shocks and empirically tests the credit crunch caused by bank failures on their client firms.

The second feature is that this research sheds light on the selection problem of the relationships between borrowers and lenders. Most current empirical banking studies do not take into account self-selection behavior; lenders choose their borrowers and borrowers choose their lenders. For example, if the client firms of failed banks invest at lower rates than other firms, this may not come from the bank failure's effect, but from firms' choices of bank. Also, if the investment rate of client firms of failed banks is higher than that of ordinary firms, the true shock will be larger than previously predicted. The empirical banking literature generally assumes that the relationships between firms and banks are randomly chosen and remain fixed because the bank–firm relationships are long-standing and unchanged. But if we relaxed the condition and we assume that selection exists, ordinary estimation may have a critical bias. This study reevaluates the relationships between firms and banks, and gauges the true shock, compared with similar firms. Also this paper finds the choice characteristics between banks and firms by interpreting the bias.

This paper has three main findings. First, bank failures reduce the investments of their client firms by nearly 30% in baseline estimation. In a recession, the clients firms' economic activity is restricted because they cannot borrow from the failed banks and the firms cannot find alternative funding under the depressed economy. This explains the mechanism of how bank failures amplify a recession from the lenders' perspective. In other words, large bank failures will affect the economy strongly as the previous literature predicted because their many client firms stagnate their activities under the serious credit crunch. Second, the high-investment firms deal with unhealthy banks. This generates a self-selection bias and the true shock

1. The definition of bank failure here is the suspension of new lending activity of a bank to their clients.

2. I use the word "credit crunch" here as the firms' status where they hardly get a loan by external shocks.

3. This paper uses two unique bank failures (Long Term Credit Bank [LTCB] and Nippon Credit Bank [NCB]) to evaluate the bank failure shock on client firms. These mainly raise money by issuing bonds, not by collecting deposits. However, I assume that whether firms borrow from a deposit-type bank or a bond-type bank does not affect the firms' investment decisions. This paper mainly considers firms' behavior under the status that "firms cannot borrow additionally from previous lenders because of bank failures." I believe that the bank-type difference does not affect the result of this paper for this purpose. The specialty of failed banks' clients is also supposed to be eliminated by difference-in-difference (DID) estimation.

is 30–80% greater than the estimates when we do not consider the self-selection. Hence, the bank-failure shock is magnified by the self-selection behavior because failing banks typically lend to high-investment firms. Third, there is no solid evidence that the firms' accessibility to other financial sources mitigates the bank-failure shock under recession. This suggests the bank lending relationship is crucial and the client firms cannot find alternative banks in a recession.

This paper proceeds as follows. Section 1 overviews the related literature. Section 2 discusses what happened in the Japanese bank failures. The data sets to be used in this study, their management, and their characteristics are presented in Section 3. In Section 4, the information of econometric methods and estimation results are provided. The robustness of results is discussed in Section 5, and Section 6 concludes.

1. PREVIOUS RELATED LITERATURE

Bernanke (1983) is the seminal paper in the research about bank loan/failure effects on the real economy. It investigates whether the financial collapse in the Great Depression affected real economy. In its estimation, a $1 million reduction in deposits of failing banks reduces the production growth rate by 0.08%, and it finds that the decrease of bank deposits by bank failures reduced the macro-level output in the 1930s in the United States. However the paper's results are questioned by other economists as to whether the recession itself causes the bank failures and whether there is clear causality between bank failures and real economy.

In response to this, Peek and Rosengren (2000) identify the loan supply shock on the real economy using a foreign banking crisis. Using the fact that the financial crisis in Japan and the economic status in the United States is unrelated, they find that the reduction of Japanese banks' lending to U.S. firms decreased the construction activity in the United States in the 1990s. In their estimation, a $100 decline in loans by Japanese banks in a given state corresponds to a decline of $111.30 in construction activity in that state.

Calomiris and Mason (2003), using an instrumental variables method, also find the effect of bank loan supply shocks on local area income. They use the state- and county-level data in the Great Depression, and regress the bank loan reduction associated with bank failures on the local area income. They find that a 1% decrease in bank loan supply growth associated with bank failures during the Great Depression decreased the income growth by 44.8%. They conclude that the loan-supply reduction distresses the local area income.

Ashcraft (2005) studies the case of bank failures in Texas in 1988 and 1992. Using ideal natural experiments that healthy banks went bankrupt due to chain bankruptcy, it identifies a negative effect of bank failures on output. The paper shows that the bank failures adversely affect the real economy independent of past local economic status and estimates that a healthy bank failure reduces income by 3.44% in the county. It also predicts that the bank failure effect mainly comes from the contraction of bank lending.

TABLE 1

COMPARISON OF PAST LITERATURE ABOUT BANK FAILURE/LOAN EFFECTS ON REAL ECONOMY

	The shock on	The shock of	Estimates	The data of
Bernanke (1983)	Production growth	Failed banks' deposit reduction ($million)	−0.8%	Country level
Peek and Rosengren (2000)	Construction	Lending reduction of Japanese banks	−111.3%	State level
Calomiris and Mason (2003)	Income growth	Loan supply growth (reduction)	−44.8%	State level
Ashcraft (2005)	Income level	Bank failures	−3.4%	County level
Minamihashi (2010)	Investment	Bank failures	−28.4%	Firm level

This paper differs from previous studies in three main ways. First, this paper gauges the direct shock on client firms to identify the mechanism of bank failures, using firm level data and a unique experimental setting. Second, it evaluates the shocks on firms that lost the relationship with banks under nationalization and tests the irreplaceability of banks after the bank failures. Third, it analyzes and reevaluates the self-selection behavior between firms and banks, and finds the properties of the relationship.

Table 1 summarizes the difference with the previous literature. This paper estimates that the client firms of failed banks reduce their investment by 28.4%, compared to similar firms under unhealthy banks. In relation to Ashcraft (2005), this result is plausible because we know the fluctuation of investment is much higher than that of GDP and the investment behavior is highly sensitive to financial conditions.

The field of finance also analyzed whether bank failures affect stock returns. Slovin, Sushka, and Polonchek (1993) first studied this topic, and Yamori and Murakami (1999), Bae, Kang, and Lim (2002), and Brewer et al. (2003) followed. In their robustness analysis, Brewer et al. considered the endogeneity problem of financial characteristics and the reverse causality regarding abnormal returns and financial characteristics assuming functional form. Also, the effect of banking health/bank loan on the real economy was considered in Gibson (1995) and Driscoll (2004). The effect of banking health on banks' activity was analyzed in Bernanke and Lown (1991), Berger and Udell (1994), Woo (2003), and Watanabe (2007). Furthermore, Fukuda and Koibuchi (2006) found that different policies of inheriting banks of failed banks changed the bankruptcy rates of client firms.

2. UNIQUE BANK FAILURES IN JAPAN

2.1 Two Difficulties in the Analysis of Bank Failures

In attempts to investigate bank failures' effect on the real economy, the previous literature encountered two difficulties: lack of data identifying which banks have which clients and shock identification.

First, the lack of data identifying which banks have which clients means that we cannot link failed banks and their firms in ordinary data. Without solid linkage, we cannot gauge the precise effect of bank failure. The previous literature tried to overcome this by substituting alternative links. For example, Slovin, Sushka, and Polonchek (1993) used the links in newspaper articles. Yamori and Murakami (1999), Bae, Kang, and Lim (2002), and Fukuda and Koibuchi (2006) used questionnaire data of research companies, and Ashcraft (2005) used the links between failed banks and their troubled counties. In the financial statements, in contrast to this, the Japanese accounting system required all listed firms to report how much and from which banks they borrowed. Using this financial statement data, this paper can detect the precise relationship between failed banks and their client firms.

Second, the shock identification indicates the inability to separate the targeted bank failure's shock from other shocks. Most bank failures are thought to induce depositors' shocks, debt/stock holders' shocks, and client firms' shocks. In addition, these direct shocks affect other unrelated entities and generate indirect local shocks. In this case, even if we had observed a bank-failure shock, we could not identify where the shock came from, and the process of how bank failures affected the real economy is still unclear. Not only are bankruptcies themselves infrequent in developed countries, but also large bank failures are rescued by governments or central banks to prevent recession under the "too big to fail" policy. Therefore, the previous literature mainly focused on bank-failure shocks on the aggregate economy, and it was difficult to identify the mechanism.

To identify the shock we want to analyze, we need a failed bank that does not contain other stakeholders' direct or indirect shocks. The unique bank failures in Japan in 1998 (LTCB and NCB) are a good case for solving the identification problem. First of all, their main financial sources were not deposits but the issuing of bonds, and the bond holders were spread via financial markets. Also, because they did not raise money from local depositors, they did not specialize their lending business in a specific area. Their branches were few in each large city and were used for their lending activity. Because both debt holders and client firms were spread over a wide area, their shocks on a specific area were relatively small. Second, the Japanese government, which nationalized those banks, reimbursed their deposits immediately, and debts on maturity. Hence, there is no actual effect on debt holders/depositors. Therefore, their failures are an appropriate way to separate loan market shocks from indirect local shocks or debt holders'/depositors' shocks.[4] Third, the bank failures were exogenous and unexpected in the data period.[5] Figure 1 compares cumulative stock returns of the two failed banks (LTCB and NCB), all banks, and unhealthy banks since January 1996.[6] This paper identified the failed banks' client firms from

4. Continental Illinois National Bank and Trust Company's bank failure in 1984 in the United States is one of the big bank failures. However, it strongly affects the Midwest area and we cannot get the lending data set.

5. The robustness of the endogeneity is also discussed in Section 5.

6. The stock returns are those with cash dividends reinvested. The measure of all banks is taken from the TOPIX bank sector index. The unhealthy banks' stock returns are the bottom 33% in bank health of the largest 17 banks that did not fail. (i.e., Daiwa, Sakura, Chuo-trust, and Mitsui-trust bank).

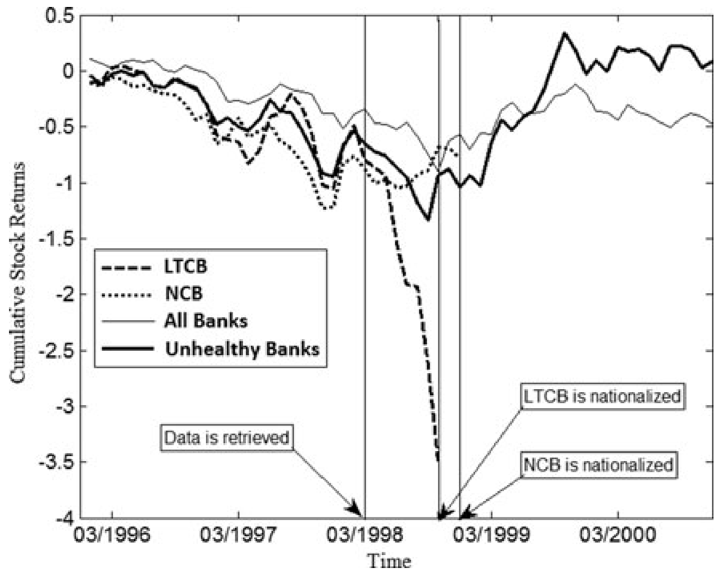

FIG. 1. Cumulative Stock Returns.

banks' loan data in March 1998, and compared their investment decisions between March 1996 to March 1998 and March 1999 to March 2001. Observing the change in stock returns, we can guess that the failures were possible for all unhealthy banks, and the choice of firms and failed banks in March 1996 to March 1998 were similar to those of the firms and unhealthy banks in the same period. In the case of NCB, the stock market could not also predict the bank failure just before it announced.

2.2 Special Nationwide Bank Failures and Their Nationalization in Japan

In October 1998, LTCB went bankrupt and in December 1998, NCB followed. Along with the bank failure of Hokkaido Takusyoku Bank (HTB) in 1997, these bank failures were the first cases of large bank failures after World War II. (HTB's branch was restricted to a local area of Japan, so this paper does not include it and its analysis.) Their loans exceeded 14 trillion yen and 7 trillion yen in March 1998, and they ranked 10th and 15th bank out of 148 banks in loan amount in Japan. They had branches all over Japan and provided loans to many publicly traded firms. Furthermore, their largest financial source was not from deposits but from issuing bonds (called "credit banks" for their specialty). They also did not have specialized areas, and their client firms spread to urban areas all over Japan. Table 2 shows the specialty of the failed nationwide banks' financial sources.

There are several reasons these banks went bankrupt. The primary reason was that the loans to the real estate, construction, and nonbank industries defaulted. The

TABLE 2

Financial Sources of the Two Failed Banks in September 1998

	LTCB(%)	NCB(%)	Nationwide banks[a](%)	Regional banks[b](%)
Total liabilities	99.3	96.1	97.5	96.7
Deposits[c]	14.1	19.6	66.0	86.7
Bond	37.6	35.5	1.3	0
Others[d]	47.6	41.0	30.2	10.0
Total equity	0.7	3.9	2.5	3.3
Total liabilities and equity	100	100	100	100

[a]Weighted average of nine Japanese nationwide banks called "city banks."
[b]Weighted average of 138 Japanese small banks called "regional banks."
[c]Deposits + CD.
[d]Allowance for doubtful accounts, call money, etc.

former boards of those banks were also convicted of accounting fraud and hid their huge debts.

As a reaction to these bank failures, the Japanese government created the decision-making policy board called the Financial Reconstruction Commission (FRC) (the members were outside politicians, lawyers, accountants, economists, etc.), and they handled the bank failures. Their main tasks were: (i) evaluating the banks' assets appropriately, (ii) restructuring and reinforcing the failed bank's assets, and (iii) selling the failed banks immediately to private banks. At the same time, all deposits were reimbursed completely the day after the bank failure and bonds were redeemed on time.

In the LTCB's case, the FRC looked into executive responsibilities for management failures, sold nonperforming loans, cut 40% of the employees, closed all of their overseas branches, and reduced the number of domestic branches. For the new loans to clients, they used rigorous assessments compared to assessments used before the bank failure because there was strong public opposition to the Japanese government's allocation of budget for failed banks. First, the new loans to the client firms were restricted only for the purpose of continuing their business. Second, they rigorously reevaluated their firms' credit rating and cut all new loans to the troubled firms. A similar response followed the failure of NCB as well. Statistics before and after the bank failure can be found in Table 3. We can observe the significant reduction of employees, branches, and lending amount after the bank failure.

After nearly 2 years of government suspension, in March 2000, LTCB was inherited by "New LTCB Partners," which was an investment group supported mainly by Ripplewood Holdings in the United States. LTCB restarted the bank as Shinsei Bank in June 2000. While the Japanese government spent about 4–5 trillion yen on LTCB to reinforce the assets in the 2 years, Ripplewood Holdings bought it for 12 billion yen.

NCB was sold to an investment group mainly supported by Softbank, which is a Japanese IT company, in September 2000, and NCB restarted its banking business

TABLE 3

FAILED BANKS' STATISTICS BEFORE AND AFTER THEIR FAILURES

	Before failure						After failure	
	3/1996	3/1997	3/1998	9/1998		3/1999	3/2000	3/2001
LTCB					B			
Total lending	18,981,796	18,860,703	15,765,016	14,641,766	A	13,614,752	7,704,725	6,183,585
Number of employees	4,405	4,259	3,988	3,762	N	3,026	2,117	1,945
Number of branches	42	41	41	39	K	33	25	24
NCB								
Total lending	10,071,724	9,080,470	7,781,830	7,596,028	F	7,209,084	4,104,221	3,092,409
Number of employees	2,937	2,820	2,303	2,202	A	2,064	1,811	1,628
Number of branches	24	24	19	19	I	19	19	18
Average of nationwide banks[a]					L			
Nationwide banks' average lending[b]	29,980,235	31,491,088	29,517,287	29,174,741	U	27,638,866	26,829,900	29,174,741
Average number of employees	15,870	14,877	14,298	14,509	R	13,836	13,258	12,751
Average number of branches[c]	391	384	380	368	E	357	338	325

NOTES: From "Zenkoku Ginko Zaimushohyo Bunseki." The unit of lending is million yen. The decrease of lending of LTCB and NCB includes the writing off of nonperforming loans.
[a]HTB is excluded for its failure.
[b]Average of nine city banks. LTCB and NCB went bankrupt in October 1998 and December 1998, and restarted their business in June 2000 and January 2001, respectively.
[c]Because LTCB and HTB did not raise money by deposits from citizens, the number of their branches is fewer than average.

the same month. The Japanese government spent 3.2 trillion yen and Softbank bought it for about 10 billion yen. Most of this money was spent to fill the gap between the nominal value and the actual value of the failed banks' loans. These were significant costs for the Japanese government.

These large bank failures were the first in Japanese history and became memorable as the "lost decade" for Japanese citizens. Whether the Japanese government's response to these bank failures was appropriate or not is still under discussion.

3. DATA DESCRIPTION

For firms' data, this paper uses the Development Bank of Japan (DBJ) database, which contains the annual financial statement data of firms. For banks' data, this paper uses the Pacific-Basin Capital Market (PACAP) database. To link firms and banks, the DBJ's loan quantity database is used. Also, to construct Tobin's Q, we use the DBJ firm data and macro data from Nikkei Needs Macro Quest.

The sample periods are from March 1992 through March 2001. The bank failures occurred in 1998, and Japanese government nationalized the banks and restricted new loans for nearly 2 years. We evaluate the difference before and after the bank failures (March 1996 to March 1998 and March 1999 to March 2001).[7] Considering the lumpy behavior of investment, we average out 2 years' values before and after the bank failure. The reason the sample period starts in 1992 is to construct values of instrument variables, which are also an average of 2 years. Regarding an attrition bias, we did not consider the failed firms in the 2 years after the bank failures. This is because, in these periods, the failed banks might lend to unprofitable firms to hide their accounting fraud. To disregard those firms, we dropped the firms that went bankrupt within 2 years after the bank failure.

For the definition of Tobin's Q, this paper uses Hayashi and Inoue's (1991) and McGuire's (2001) "multiple Tobin's Q." McGuire is the improved version of Hayashi and Inoue, and we use McGuire's method with minor improvements. The method to calculate those variables is different from an ordinary single Tobin's Q. First, they separate the new acquisition of assets and sales of existing assets using unique Japanese data. Second, the asset values are calculated in the different five asset types. Third, they consider the tax system that supports firms' investment. The advantage of calculating Q by this method is to reduce the measurement error of Tobin's Q. It is well known that there exists huge measurement errors in Tobin's Q, and this method reduces the noise in both the numerator and the denominator of standard Tobin's Q. For cash-flow rates, this paper uses the definition of Hoshi, Kashyap, and Sharfstein (1991). For investment rate, this paper uses the new asset purchase divided by the calculated real assets.

7. After nearly 2 years of the nationalization, the Japanese government sold the banks to the private sector. The investment behaviors of the client firms during this period may have depended on the inherited banks' policy; therefore, we analyze the period only under the nationalization.

The bank failure dummy is the key variable in this paper. The definition of the failure dummy is a firm that deals with failed banks equals one; otherwise, it equals zero.[8] I only consider the two failed banks (LTCB and NCB) and delete the client firms of other failed banks. The matching method with banks and firms is as follows. First, I sorted banks by loan amount for each firm, and I defined banks whose lending amounts are more than 80% of the largest loan bank's lending as significant banks.[9] We assume that these banks will affect the firms' investment decisions. This connection is constructed by the actual loan quantity and does not restrict the number of banks who affect firms' decisions. The bank failures were in October and December 1998, and I used the closest loan data in March 1998. The robustness of this connection is considered in Section 5. The client firms of failed banks make up 35 out of 904 firms.

The same set of shocks, such as industry shocks or regional shocks, may have separately led to the bank failures themselves or/and to lower investment from the failed banks' clients. Tables 4 and 5 depict the failed banks' clients characteristics to check these properties. The distribution of industries and the distribution of geographic areas are widely spread.[10] This information shows that client firms are not concentrated in a specific industry or region.

A disputable variable among economists is the measurement of bank health. Some papers used the capital asset ratio from accounting data and other papers used the market values computed from stock price. This paper uses the market-type definition of Hosono and Sakuragawa (2003) (similar to Bernanke and Lown 1991 and Peek and Rosengren 2005), which is the equity capital evaluated by the stock market divided by the bank's total asset. This is because Hosono and Sakuragawa (2003) reported that the market-base definition is most reliable since unhealthy banks have an incentive to disguise their bank health using accounting. Table 6 shows the consistency of three bank-health measures (credit rating, Bank for International Settlements (BIS) ratio, and market capital asset ratio) of 17 large banks in March 1998. The credit rating data are taken from Moodys,[11] and the BIS ratio and market capital asset ratio are

8. Another option to evaluate bank-failure shock is to use the value of how much the client firms borrow from the failed banks. The reason I use a dummy, not the value, is to analyze a bank failure's shock on general firms. If a firm wants to invest, it mainly borrows from banks, issues equity, or issues bonds. If it intends to borrow, I assume that it will apply to the large-share banks that issued the current loans. In the literature of policy evaluation of other fields, they also mainly use the dummy-variable-type analysis to evaluate the effect, rather than values that reflect the deepness of the relation. In Section 4, I also consider the borrowing amount itself.

9. The reason I use the borrowing share of total borrowings instead of the borrowing amount compared to assets is twofold. First, most of the previous literature used the questionary data on the order of significant banks, and I follow them with unique loan data. This is because some firms has a strong relationship with some banks, and even if firms do not borrow significant amounts now, it is possible that the banks' conditions affect the firms' behavior in the future. Second, I want to estimate the effects on general client firms, not the effects on specific firms which rely heavily on banks.

10. This paper indentifies the firms' region from the place where their head offices are located. Approximately 40% of firms have their headquarters located in Tokyo, as some of them are nationwide firms. This fact coincides with the aggregate data of listed firms.

11. I do not use the credit-rating data as bank-health measure in the regression because I cannot take all of the small banks' credit-rating data.

TABLE 4

Industries of Failed Banks' Client Firms

Industries	Number
Agriculture, forestry, fishing, and hunting	1
Mining	2
Construction	1
Manufacturing	21
(Nonmetallic mineral products)	(3)
(Primary metals)	(2)
(Machinery)	(1)
(Electrical equipment, appliances, and components)	(5)
(Motor vehicles, bodies and trailers, and parts)	(1)
(Food and beverage and tobacco products)	(1)
(Textile mills and textile product mills)	(2)
(Petroleum and coal products)	(1)
(Chemical products)	(2)
(Plastics and rubber products)	(3)
Retail trade	2
Transportation and warehousing	6
(Rail transportation)	(1)
(Water transportation)	(1)
(Transit and ground passenger transportation)	(1)
(Warehousing and storage)	(3)
Arts, entertainment, recreation, accommodation, and food services	2
Total	35

TABLE 5

Geographic Areas of Failed Banks' Client Firms

State	Number	%	All listed firms[a]
Tokyo	14	40.0%	48.9%
Osaka	8	22.9%	12.8%
Kanagawa	4	11.4%	5.1%
Fukui	2	5.7%	0.4%
Kyoto	2	5.7%	1.8%
Saitama	2	5.7%	2.0%
Aichi	1	2.9%	6.3%
Niigata	1	2.9%	1.1%
Yamanashi	1	2.9%	0.7%

[a]The number of all listed firms is taken from http://www.rs-kumamoto.com/JK/.

taken from banks' financial statement data. The BIS ratio is the book-based capital asset ratio defined by BIS. The consistency between the credit rating and the market capital asset ratio is observable, but the BIS ratio is different from other measures.

As in the previous literature, this paper takes only the March accounting month to avoid unsequential account timing (most Japanese firms close their books in March.) This paper also uses continuously existing firms from 1992 to 2001. I removed the firms whose Tobin's Q cannot be constructed because of data deficiency and the firms whose significant bank health cannot be constructed. This is because some small

TABLE 6

THE VALIDITY OF BANK HEALTH MEASUREMENTS

Name	Credit rating	BIS	MCAR
Bank of Tokyo_Mitsubishi	A1 (1/17)	8.53 (16/17)	8.64 (3/17)
Nippon Trust Bank	A2 (2/17)	13.48 (2/17)	13.54 (1/17)
Sumitomo Bank	A3 (4/17)	9.23 (13/17)	6.98 (4/17)
Ind. Bk of Japan	A3 (4/17)	10.26 (8/17)	4.98 (8/17)
Dai_Ichi Kangyo Bank	Baa1 (6/17)	9.08 (15/17)	5.52 (6/17)
Sakura Bank	Baa1 (6/17)	9.12 (14/17)	3.42 (13/17)
Asahi Bank	Baa1 (6/17)	9.38 (12/17)	4.34 (10/17)
Fuji Bank	Baa1 (6/17)	9.41 (11/17)	4.54 (9/17)
Tokai Bank	Baa1 (6/17)	10.25 (9/17)	5.21 (7/17)
Mitsubishi Trust Bank	Baa1 (6/17)	10.35 (5/17)	8.81 (2/17)
Mitsui Trust Bank	Baa2 (11/17)	10.40 (4/17)	3.12 (16/17)
Sumitomo Trust Bank	Baa2 (11/17)	9.89 (10/17)	6.56 (5/17)
LTCB*	Baa3 (13/17)	10.32 (6/17)	2.23 (17/17)
Daiwa Bank	Baa3 (13/17)	10.29 (7/17)	3.21 (15/17)
Chuo Trust Bank	Baa3 (13/17)	12.73 (3/17)	3.35 (14/17)
NCB*	Baa3 (13/17)	8.25 (17/17)	3.66 (12/17)
Yasuda Trust Bank	Baa3 (13/17)	13.56 (1/17)	3.8 (11/17)

NOTES: These data are from 1998.3. The credit rating is taken from Moodys. The BIS ratio is taken from "Zenkoku Ginkou Zaimu Syohyo." The definition of MCAR is $\frac{\text{\# of shares * stock price}}{\text{Total liability + (\# of shares * stock price)}}$, taken from Hosono and Sakuragawa (2003). The numbers in parentheses show the ranking of the 17 banks.

banks are listed on the local stock market, but their data cannot be retrieved from the PACAP database. I also deleted firms whose significant banks are government banks. To eliminate the outliers, this paper deletes 1% of independent variables, dependent variables, and instrument variables ($I_{i,t}/K_{i,t-1}$, $Q_{i,t}$,$CF_{i,t}/K_{i,t-1}$, $Q_{i,t-1}$, $Q_{i,t-2}$) for both control and treatment groups, which is discussed in Section 4.2. This paper eliminates outliers for both groups since the number of observations for the failed banks' client firms is small and will be affected heavily by outliers. This paper also deletes the clients of other failed banks in 1996–2000. Figure 2 is the plot of the dependent variable on each independent variable. The upper panels are before eliminating outliers, and lower panels are after eliminating outliers. We can see that the deleting outliers was successful. Table 7 is the main variables' statistics.

4. EMPIRICAL METHOD AND THE RESULT

4.1 Basic Model

This paper assumes the following Tobin's Q equation and this is consistent with the previous literature.

$$\frac{I_{i,t}}{K_{i,t-1}} = \beta_0 + \beta_1 Q_{i,t} + \beta_2 \frac{CF_{i,t}}{K_{i,t-1}} + \varepsilon_{it}, \tag{1}$$

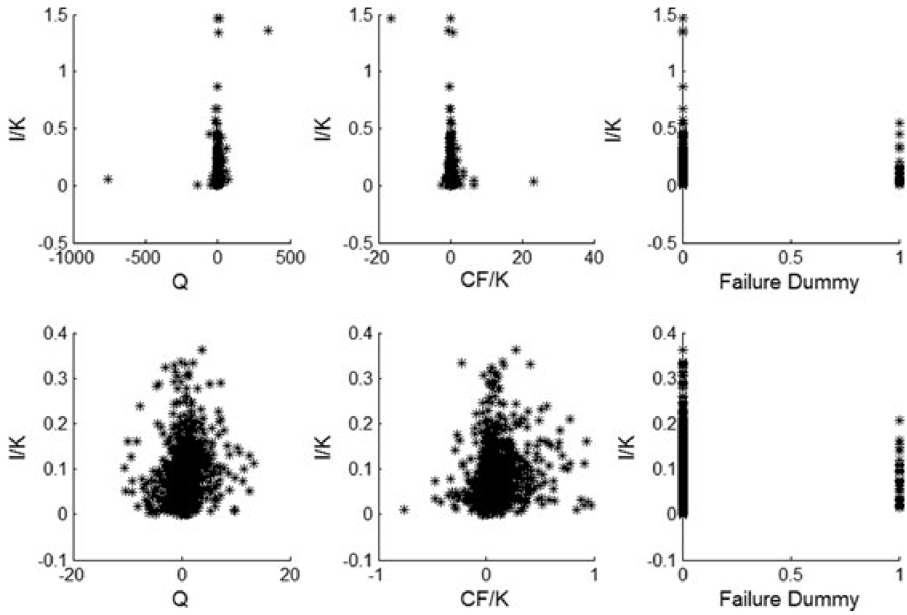

FIG. 2. Deleting Outliers.

NOTE: Top panel is before the deletion, and the bottom panel is after the deletion. Significant level is 1%

TABLE 7

DESCRIPTIVE STATISTICS FOR ALL SAMPLES (t = 1996–98, 1999–2001)

	Mean	S.D.	Min	Max
I/K	0.095	0.056	0	0.344
$\Delta I/K$	−0.007	0.067	−0.277	0.285
Q	0.931	2.66	−12.34	15.06
ΔQ	−0.69	2.80	−12.58	15.79
CF/K	0.101	0.14	−0.48	0.81
$\Delta CF/K$	−0.03	0.12	−0.61	0.71
Number of dealing banks	11.12	11.20	0	127
Number of significant banks	1.13	0.86	0	7
Sales	19.8	63.5	0	144
Borrowing/sales	0.25	0.38	0	3.79
Bond dummy	0.57	0.49	0	1

NOTES: The number of observation is 1,808. The number of firms is 904.

where $K_{i,t}$ is the capital, $I_{i,t}$ is the investment, $Q_{i,t}$ is Tobin's Q at the beginning of the year, $\frac{CF_{i,t}}{K_{i,t-1}}$ is the cash flow rate that measures the firm's individual financial constraint.

To evaluate the bank-failure shock, we add a bank-failure dummy (*Failure dummy*$_i$) to the equation, which equals 1 if the firm's bank failed. This bank failure dummy is used as a suspension of the bank relationship as a result of the bank failures. This paper also adjusts the standard model with a time-specific business cycle shock (T) and individual effects of firms (α_i).

$$\frac{I_{i,t}}{K_{i,t-1}} = \beta_0 + \beta_1 T + \beta_2 Q_{it} + \beta_3 \frac{CF_{i,t}}{K_{i,t-1}} + \beta_4 Failure\ dummy_i + \alpha_i + \varepsilon_{it}. \tag{2}$$

I use a DID estimator for the before–after analysis.

$$\begin{cases} \dfrac{I_{i,t}}{K_{i,t-1}} = \beta_0 + \beta_1 T + \beta_2 Q_{it} + \beta_3 \dfrac{CF_{i,t}}{K_{i,t-1}} \\ \qquad + \beta_4 Failure\ dummy_i + \alpha_i + \varepsilon_{i,t} & \text{(after the shock)} \\ \dfrac{I_{i,t-1}}{K_{i,t-2}} = \beta_0 + \beta_1 (T-1) + \beta_2 Q_{it-1} \\ \qquad + \beta_3 \dfrac{CF_{i,t-1}}{K_{i,t-2}} + \alpha_i + \varepsilon_{i,t-1} & \text{(before the shock)} \end{cases}$$

Taking the first difference, the above equations become

$$\Delta \frac{I_{i,t}}{K_{i,t-1}} = \beta_1 + \beta_2 \Delta Q_{i,t} + \beta_3 \Delta \frac{CF_{i,t}}{K_{i,t-1}} + \beta_4 Failure\ dummy_i + \Delta\varepsilon_{i,t}. \tag{3}$$

The standard Q theory with perfect competition implies that β_3 and β_4 equal zero. However, most of the literature in banking and finance predicts $\beta_3 > 0$ and $\beta_4 < 0$.[12]

4.2 Self-Selection Bias between Firms and Banks

The selection behavior among lenders and borrowers. This paper removes the bias caused by selection between the firms and banks. However, is considering the selection truly important? Some of the literature assumes that the relationships between firms and banks are long and fixed, and the relationship will not be changed frequently. Table 8 depicts the frequency rate for firms that changed their first banks. In the 1990s in Japan, nearly 25–30% of firms changed their first bank within 3 years.[13]

12. In other specifications, I might consider inserting a bank-health measure, an investment-growth fixed effect, or a year dummy. First, I avoid inserting the bank health because I cannot define the bank health of failed banks after the bank failures. I selected the control group from the client firms of bad health banks in 1998; therefore, this selection reduces the bank-health effect. Second, to take the individual fixed effect in investment growth, I have to expand the sample period, and it reduces the treatment sample heavily. To keep the sample at a statically sufficient level, I avoid the specification. To test this, I also conduct a level-type estimation using propensity score matching (PSM) method in a technical appendix, and it indicates simliar results with growth level estimation. Third, I use T in two-period data in the equation, and this is equivalent to inserting a year dummy.

13. I define the first bank using the borrowing amount here. The long-term borrowing amount is used because the DBJ database does not contain the short-term borrowing amount in the early 1990s. All of the client firms whose first banks are merged or failed in the period are removed from the sample. Only the firms that survived the period are taken in the sample.

TABLE 8

Frequency of Changing First Bank in 1990s

Period	# of change	# of all firms	%
1990.3–1993.3	290	1013	28.6
1993.3–1996.3	352	1226	28.7
1996.3–1999.3	259	1004	25.7

Notes: The firms whose first bank has merged or failed are removed. Only the firms that survived for the period are included.

TABLE 9

Difference between Client Firms

	i	q	i/q	$\Delta i/q(\%)$
		1994.3–1996.3		
Bottom 33% banks' clients	0.154	2.573	0.060	234%
Middle 33% banks' clients	0.146	2.644	0.055	164%
Upper 33% banks' clients	0.151	3.613	0.041	129%
		1996.3–1998.3		
Bottom 33% banks' clients	0.094	0.738	0.127	113%
Middle 33% banks' clients	0.091	0.922	0.099	80%
Upper 33% banks' clients	0.091	1.206	0.075	81%
		1998.3–2000.3		
Bottom 33% banks' clients	0.091	0.743	0.122	−5%
Middle 33% banks' clients	0.084	0.968	0.087	−12%
Upper 33% banks' clients	0.089	1.056	0.084	11%

Notes: The median value in the group is taken. The firms that do not borrow are eliminated.

The characteristics of client firms under banks with different bank-health levels are in Table 9. In each period, it is clear that the clients of unhealthy banks are the firms with low Tobin's Q (q) and high investment rates adjusted by Tobin's Q (i/q). This suggests that client firms with low potential investment opportunities but that invest high tend to deal with the unhealthy banks. This evidence supports the importance of considering the self-selection behavior.

Taking into account the firms'/banks' selection behavior, the estimates β_4 (the coefficient of bank-failure dummy) may have a bias. If high investment growth/level firms choose to deal with unhealthy banks or the unhealthy banks approved risky lending to recover from unhealthy status, the shock to firms may be larger than expected. By checking the direction of this bias, we can observe the characteristics of the relationship between firms and banks.

I have several predictions on the choices of banks and firms. If I roughly categorize, two relationships can be predicted. The first prediction is that the high investment growth firms tend to deal with healthy banks. Petersen and Rajan (1995) showed that banks want to foster high growth young firms and earn profit after the firms mature. Dewatripont and Maskin (1995) also showed that firms have an incentive to borrow from healthy banks because these banks can help client firms when firms fall into financially troubled conditions. Another prediction is that the high investment growth/level firms tend to borrow from unhealthy banks. This is because unhealthy banks want to resuscitate their status and they may allow risky loans. Also, firms with large and risky plans may be rejected by healthy banks. In this case, the high potential investment growth/level firms are doing business with unhealthy banks and those unhealthy banks allow those firms' high investments.

Bias components and the way they affect. To simplify the notation in the discussion of the DID estimator's bias components, I define the following: i_{0it-1} is the firm i's potential investment rate (i) before 1998 ($t-1$) and the firm i's significant bank did not fail (0). Also, i_{1it} is the firm's investment rate after 1998 (t) and the firm's significant bank is failed (1). i_{0it} is defined in the same way except that its bank did not fail in 1998. $D_{it'}$ is the decision of firm i whether it borrows from the failed bank (if it does, $D_{it'}$ is 1) in 1998. The covariate X_{it} is Tobin's Q and cash-flow ratio. The component of average treatment effect on the failed banks client (ATE_1) can be described as follows.

$$\begin{aligned} ATE_1 = {} & E(i_{1it} - i_{0it-1}|D_{it'} = 1, X_{it}) - E(i_{0it} - i_{0it-1}|D_{it'} = 0, X_{it}) \\ & - [E(i_{0it} - i_{0it-1}|D_{it'} = 1, X_{it}) - E(i_{0it} - i_{0it-1}|D_{it'} = 0, X_{it})]. \end{aligned}$$

The bias is $E(i_{0it} - i_{0it-1}|D_{it'} = 1, X_{it}) - E(i_{0it} - i_{0it-1}|D_{it'} = 0, X_{it})$. In this study, I predict that the ATE_1 is negative, because bank failures affect the clients' investment negatively. If low investment growth firms tend to deal with failed banks, then $E(i_{0it} - i_{0it-1}|D_{it'} = 1, X_{it}) < E(i_{0it} - i_{0it-1}|D_{it'} = 0, X_{it})$ and the true shock is smaller than ordinary estimates. If the firms with high potential investment growth tend to deal with failed banks, then $E(i_{0it} - i_{0it-1}|D_{it'} = 1, X_{it}) > E(i_{0it} - i_{0it-1}|D_{it'} = 0, X_{it})$. In this case, the true shock is larger after taking into account the self-selection bias.

The identification condition for the DID estimator to evaluate ATE_1 is

$$E(i_{0it} - i_{0it-1}|D_{it'} = 1, X_{it}) = E(i_{0it} - i_{0it-1}|D_{it'} = 0, X_{it}).$$

In other words, this condition states that if no bank failed, there are no differences in investment growth between the firms that borrowed from failed banks and the firms that did not borrow from the failed banks, conditional on Tobin's Q and cash flows. This is the weaker version of the unconfoundness assumption. These models and conditions are used in Heckman et al. (1998).

Compared to ordinary least squares (OLS), the DID estimation routine removes the self-selection bias. However, Dehejia and Wahba (1999) claim that the DID estimator

TABLE 10

SAMPLE STATISTICS OF TREATMENT AND CONTROL GROUP BEFORE THE BANK FAILURE

	Control ($N_1 = 173$)		Treatment ($N_0 = 35$)		Control and treatment	Full sample ($N = 869$)		Full and treatment
	Mean	(S.D.)	Mean	(S.D.)	diff / S.D.	Mean	(S.D.)	diff / S.D
Q_t	0.77	2.03	1.20	1.70	−0.22*	1.26	2.80	−0.03*
CF/K	0.07	0.10	0.06	0.11	0.10*	0.12	0.14	−0.54
Number of significant banks	1.50	0.72	1.26	0.51	0.35	1.02	0.86	0.46
Sales	1.74	5.39	7.87	15.70	−0.86	20.7	68.8	−0.72
Borrowing/sales	0.19	0.30	0.32	0.34	−0.42	0.15	0.27	0.50
Bond_{t-1}	0.62	0.49	0.54	0.51	0.16*	0.64	0.48	−0.20*
Q_{t-1}	0.94	2.42	1.13	2.65	−0.08*	1.61	3.15	−0.18*
Q_{t-2}	3.46	3.56	3.43	3.54	0.01*	4.84	5.31	−0.39
I/K	0.09	0.06	0.10	0.07	−0.16*	0.10	0.05	0.00*

NOTES: * is less than 0.25. Main covariates, Q_t, and CF/K satisfy the criteria. Treatment group is the client firms of the failed banks. The firms whose bank health is unknown are included in the full sample. The control group is the firms whose weighted banks' health is in the bottom 33%. The control group is taken from the group whose banks' health is known. "Full" and "Control" do not include the treatment group.

relies heavily on the control group; thus, the control group must be chosen carefully.[14] To satisfy the identification condition, I selected a control group. My control group was composed of firms whose significant banks' health was in the bottom 33% in the end of 1998.[15] If a firm had more than one significant bank, I took the weighted average of their banks' health by borrowing amounts. By controlling the bank's health before the shock, I can randomize firms'/banks' relationship and evaluate the true shock.

Table 10 provides the descriptive statistics of the treatment group and the control group. We can see that the procedure used to select the control group is valid. Imbens and Wooldridge (2008) recommend choosing the control group where the mean difference of covariates divided by its standard error is less than 0.25. This is because when there exists a large difference within the two groups in covariate distribution, linear regressions with a dummy for the treatment variable are affected heavily by extrapolation, and this causes a significant bias due to misspecification of the model. However, this issue is resolved if the ratio is less than 0.25.[16]

4.3 Basic Results: Bank Failures' Effect on Client Firms

Tables 11 and 12 contain basic results showing whether or not clients' investments are affected by bank failures.

Table 11 contains results from the level regressions, which do not consider self-selection. In the first column are results from the regression of the standard Q model,

14. The selection of a precise control group also enables me to get the robustness to unobservables, because it randomizes the treatment.

15. The robustness of selection of the control group is considered in Section 5.

16. Main covariates, Tobin's Q, and cash flow rate satisfy this criteria.

TABLE 11

Level Estimation Results without Self-selection Adjustment

	(1) OLS without failure	(2) OLS with failure	(3) GMM with failure
Const	0.0855**	0.0861**	0.0872**
	(0.0021)	(0.0021)	(0.0022)
Q_{it}	0.0029**	0.0029**	−0.0007
	(0.0007)	(0.0007)	(0.0018)
$\frac{CF_{i,t}}{K_{i,t-1}}$	0.0337**	0.0333**	0.0410**
	(0.0109)	(0.0109)	(0.0134)
Failure dummy	–	−0.0156	−0.0148*
	–	(0.0097)	(0.0082)
R^2	0.0302	0.0327	–
J(p-value)	–	–	0.8027
Endogeneity	–	–	Q_{it}

Notes: **Significant at 5%. *Significant at 10%. The standard errors are in parentheses. Dependent variable is i_{it}. Instrument variables are $Q_{i,t-1}, Q_{i,t-2}$.

and the coefficients are similar to those in the past literature such as Hoshi, Kashyap, and Scharfstein (1991), Gibson (1995), and Hayashi (1997). The second column contains results after the bank-failure dummy is added. The coefficient on the bank-failure dummy is negative but insignificant. The third column accounts for the endogeneity of Tobin's Q. The failure dummy becomes significant at the 90% level. This result indicates that the bank failure reduces the client firms' investment by about 15.6%, because the average investment rate in this period is 0.095.

Table 12 contains the results from DID estimations, which account for self-selection. Columns labeled "Full" uses the entire data set. Columns labeled "Control" use the control group selected from the client firms of unhealthy banks. The first estimation is the regression without the bank-failure dummy. The results are similar to those in the past literature.

The second estimated equation in Table 12 includes the bank-failure dummy. Standard theories of banking suggest that the bank-failure dummy's coefficient should be significantly negative because failed banks' clients will be in a credit crunch and have to invest under more difficult circumstances. In both the full and control samples, the failure dummy's coefficient is significantly negative. Comparing the full and control samples, the bank-failure shock is larger in the control sample.

The third and fourth sets of results are from models that accounts for the endogeneity of Tobin's Q. The value of the failure dummy coefficient is −0.027 and the average investment rate is 0.095 in the data period, so the client firms of failed banks reduced their investment by 28.4%. In the selected control group, the effect of Tobin's Q becomes insignificant. These results are similar to the lending function analysis by Hosono and Sakuragawa (2003) and suggest that investment decisions are not affected by ordinary profits. Rather, the condition of the banks is important for those firms. The difference between the third and fourth sets of estimates is whether the estimation routine allows for conditional heteroskedasity. Instrumental variables are

TABLE 12

DID Estimation Results with Self-Selection Adjustment

	(1) DID without failure		(2) DID with failure		(3) DID by 2SLS		(4) DID by GMM	
	Full	Control	Full	Control	Full	Control	Full	Control
$Const$	−0.0039*	−0.0035	−0.0029	0.0013	−0.0026	−0.0007	−0.0027	−0.0001
	(0.0023)	(0.0049)	(0.0024)	(0.0053)	(0.0026)	(0.0070)	(0.0026)	(0.0067)
ΔQ_{it}	0.0032**	0.0049*	0.0032**	0.0051*	0.0036**	0.0019	0.0037*	0.0024
	(0.0008)	(0.0027)	(0.0008)	(0.0027)	(0.0020)	(0.0079)	(0.0022)	(0.0072)
$\Delta \frac{CF_{i,t}}{K_{i,t-1}}$	0.0327*	0.0561	0.0357*	0.0663*	0.0345*	0.0724*	0.0341	0.0741
	(0.0185)	(0.0390)	(0.0186)	(0.0389)	(0.0192)	(0.0413)	(0.0225)	(0.0502)
$Failure\ dummy$	–	–	−0.0235**	−0.0272**	−0.0235**	−0.0269**	−0.0234**	−0.0270**
	–	–	(0.0115)	(0.0122)	(0.0115)	(0.0121)	(0.0103)	(0.0114)
R^2	0.0229	0.0292	0.0274	0.0525	–	–	–	–
J(p-value)	–	–	–	–	0.4403	0.3483	0.3870	0.4483
Endogeneity	–	–	–	–	ΔQ_{it}	ΔQ_{it}	ΔQ_{it}	ΔQ_{it}
Conditional heteroskedasticy	No	No	No	No	No	No	Yes	Yes

Notes: **Significant at 5%. *Significant at 10%. The standard errors are in parentheses. Dependent variable is Δi_{it}. Instrument variables are $Q_{i,t-2}, Q_{i,t-3}$. "Control" is the sample of firms whose bank health is in the bottom 33%.

chosen from past Tobin's Q, and the J-statistic predicts that the specification test passes. Concerning the generalized method of moments (GMM) estimation, this paper uses a basic two-step type. These models are based on Blundell et al. (1992) and Hayashi (1997). The results are the same, even when we consider the endogeneity of Tobin's Q.

Econometric theory suggests that the self-selection effect will be largest using OLS and smallest using DID with a valid control group. From Tables 11 and 12, we know that bank failures decrease investments of the client firms by about 30% and the OLS estimates, which does not consider self-selection, has 80% negative bias.[17] Because the bias negatively affects the true estimate, the results suggest that high investment growth firms choose/are chosen by unhealthy banks.

We can summarize the results of Tables 11 and 12 as follows: (i) high investment growth firms deal with unhealthy banks, and (ii) modifying the self-selection bias, the bank failures decrease the investments of the client firms by approximately 30%. This is a significant value. Therefore, we can confirm that bank failures can trigger recessions or deepen recessions because they impose a severe credit crunch on their clients, as previous theory predicts.

4.4 The Depth of Bank Failures' Shock Based on Firms' Characteristics

Next, we consider the relationship between bank failures' shocks and their client firms' characteristics. The close relationships between failed banks and other financial sources may change the impacts due to the bank failures' shock. This section uses the same model as the previous section but focuses on characteristics with failed bank borrowing share, number of dealing banks, sales, bond issuing dummy, and borrowing ratio. To confirm that the cross-term significance does not come from the target variable itself, the target variable[18] itself is added separately. The results are in Tables 13 and 14.

$$\Delta \frac{I_{i,t}}{K_{i,t-1}} = \beta_0 + \beta_1 \Delta Q_{it} + \beta_2 \Delta \frac{CF_{i,t}}{K_{i,t-1}} + \beta_3 Failure\ dummy$$
$$+ \beta_4\ \textit{Target variable} + \beta_5 Failure\ dummy \times \textit{Target variable} + \varepsilon_{it}.$$

The impacts on the clients with high failed bank borrowing. In this section, I test whether the bank-failure shock varies with size of the bank's loans. The high failed bank-ratio dummy variable equals to one if the failed banks' loan divided by total loans is in the top quarter of the client firms. The bank-failure shock may be

17. The DID's coefficients are between the 90% and 95% confidence intervals of OLS; therefore, this difference of estimates is significant. The technical appendix also suggests this significancy has robustness to endogeneity.

18. In the estimation on the cross-term with high failed bank borrowing dummy, we cannot take the failed bank borrowing data of nonclient firms. Therefore, the first bank borrowing ratio is taken as the adjustment variable.

TABLE 13

CROSS-TERM EFFECT WITH FAILED BANKS' SHARE

	Failed banks' share	
Sample	Full	Control
Const	−0.0016	−0.0014
	(0.0040)	(0.0106)
ΔQ_{it}	0.0036*	0.0014
	(0.0022)	(0.0079)
$\Delta \frac{CF_{i,t}}{K_{i,t-1}}$	0.0342	0.0770
	(0.0225)	(0.0495)
Failure dummy	−0.0362**	−0.0393**
	(0.0104)	(0.0115)
High failed-bank ratio dummy	−0.0012	−0.0009
	(0.0035)	(0.0106)
Failure dummy×High failed-bank ratio dummy	0.0566**	0.0535**
	(0.0235)	(0.0234)
J (p-value)	0.4023	0.4602

NOTES: **Significant at 5%. *Significant at 10%. The standard errors are in parentheses. Instrument variables are $Q_{i,t-2}, Q_{i,t-3}$. Endogenous variables is ΔQ_{it}. Dependent variable is $\Delta\, i_{it}$. "Control" is the sample of firms whose bank health is in the bottom 33%.

TABLE 14

CROSS-TERM EFFECT WITH FIRM CHARACTERISTICS

Sample	(1) Number of banks control	(2) Sales control	(3) Bond control	(4) Borrowing/sales control
Const	−0.0014	0.0029	0.0080	0.000
	(0.0067)	(0.0068)	(0.0087)	(0.0078)
ΔQ_{it}	0.0013	0.0014	0.0017	0.0017
	(0.0069)	(0.0075)	(0.0071)	(0.0071)
$\Delta \frac{CF_{i,t}}{K_{i,t-1}}$	0.0770	0.0679	0.0742	0.0769
	(0.0499)	(0.0500)	(0.0489)	(0.0519)
Failure dummy	−0.0329**	−0.0319**	−0.0410*	−0.0380**
	(0.0115)	(0.0137)	(0.0252)	(0.0177)
Low-number dummy	−0.0044	–	–	–
	(0.0130)	–	–	–
Failure dummy ×	0.0241	–	–	–
Low-number dummy	(0.0315)	–	–	–
Low-sales dummy	–	−0.0130	–	–
	–	(0.0116)	–	–
Failure dummy ×	–	0.0192	–	–
Low-sales dummy	–	(0.0207)	–	–
No bond dummy	–	–	−0.0172*	–
	–	–	(0.0095)	–
Failure dummy ×	–	–	0.0258	–
No bond dummy	–	–	(0.0270)	–
High-borowing dummy	–	–	–	−0.0011
	–	–	–	(0.0119)
Failure dummy ×	–	–	–	0.0238
High-borrowing dummy	–	–	–	(0.0224)
J (p-value)	0.4767	0.3193	0.2710	0.4212

NOTES: **Significant at 5%. *Significant at 10%. The standard errors are in parentheses. Instrument variables are $Q_{i,t-2}, Q_{i,t-3}$. Endogenous variables is ΔQ_{it}. Dependent variable is Δi_{it}.

larger for firms that borrow intensively from failed banks. The results in Table 13 indicate that the cross-terms have significance but turned out positive contrary to my prediction. This may be a result from dividing the small sample to construct the dummy.[19]

The relationship between firms' characteristics and bank failures' shock. Table 14 analyzes the relationship between bank-failure shocks and client firms' accessibility to other financial sources.

The first equation estimates tests whether accessibility to other banks mitigates the shock. If firms have relationships with other banks, the effect of bank failure on those firms might be weaker. As a proxy for access to other banks, I use the number of banks the firms borrowed from before the bank failures. If the firm had dealt with many other banks, those banks would have had information on the firm and would have easily lent to them. I create a dummy that equals one if the number of banks the firm deals with is in the bottom quarter, and zero otherwise. The results suggest that firms' accessibility to other banks does not weaken the bank-failure shock.

Estimating the second equation tests the importance of the asymmetric information. In standard banking theories, for firms whose information is hidden from the public, the effect of the bank failures should be larger. Unknown firms have fewer financial sources; therefore, they will be in a more difficult situation if their banks cannot lend to them. I use a low-sales dummy (if the sales are in the bottom quarter, it is one) as the proxy of the asymmetric information. If sales are lower, there may be more asymmetric information, and the bank failure effect may be strong. While the theories suggest this cross-term should be significantly negative, the results are insignificant. This result does not change if I use the bottom-half criteria.

The third equation checks whether past bond issuing mitigates the credit crunch. The no-bond dummy equals one if the firm has not issued bonds before, and zero otherwise. Banking theories predict that the cross-term's coefficient is negative. Firms that have no option to issue bonds will be affected more by bank failures. The result is also insignificant. Whether the firm can issue bonds easily or not is unrelated to the bank-failure shock.

The fourth equation estimates whether the firms' dependence on bank loans change the impact of the bank-failures' shock. The high borrowing/sales ratio dummy variable equals one if the total loan divided by the firms' sales is in the top quarter. I predict that firms highly dependent on banks suffer more from the bank failures. The results suggest that the cross-terms are insignificant.

From the above results, I conclude that there is no evidence that the existence of other financial sources mitigates the bank-failure shock. These results are robust to changing the dummy criteria from 25% to 50% and using the full sample.

19. Keep in mind that these results come from the data of listed firms, in recessions and limited sample.

5. ROBUSTNESS CHECKS

This section examines the robustness of the results. I consider five robustness checks.

The first considers robustness to the instrumental variables and potential endogeneity of the covariates. Using models in Blundell et al. (1992), I check the validity of those variables. The results are in Table 15. The first and second equations examine instrumental variable robustness. I confirm that the estimates are stable after adding new instruments. The third equation checks the difference type instrument variable. The fourth considers the case when the cash-flow rate is endogenous. In every case, the OLS estimation yields the lowest shock and the DID with a selected control group is the highest. These results are significant; therefore, our results are robust to the choice of instrument and endogenous variable selection on covariates.

The second check examines the robustness of the bank-failure dummy. The bank-failure dummy equals one if one of the firm's significant banks failed. I define the significant banks for a firm as (i) the bank from which the firm borrows the most and (ii) banks that lend the firm more than 80% of the amount lent by the bank in (i) Using different percentage thresholds for (ii), I check the robustness to the dummy construction. The results are in Table 16. All of the regressions use the GMM in Section 4. Even when the percentage threhold in (ii) is set high, the results have similar properties to those Tables 11 and 12. When the percentage in criterion (ii) is low, the bank-failure shock disappears. The shock likely disappears because I include client firms with little relationship to the failed banks.

The third robustness check considers choice of the control group. I define the control group are the client firms whose banks' health is in the bottom 33%. Table 17 considers control groups constructed using different percentages. When I change the criterion to the bottom 10%, the effect is larger. If I use the bottom 50% criteria, the estimates are similar to the estimation results that do not select the control group.

The fourth robustness check considers investment level bias and the selection of control group. Using propensity score matching (PSM), I can estimate the effect assuming the existence of level bias. The results are also robust to the selection of control group. The results from PSM estimation are similar to results using the DID estimation.

The fifth check is the robustness to the endogeneity of the bank-failure dummy. To solve the endogeneity problem, this paper uses the DID estimator, selects the control group carefully, and attempts to randomize the occurrence of bank failures between the treatment group (failed banks' clients) and control group (unhealthy banks' clients). Inserting the individual fixed effect term and using DID method, I also removed the endogeneity caused by unobservables. To confirm the robustness of the endogeneity of bank-failure dummy, I used the Rosenbaum (2002) method in the PSM estimation and gauged the effect of endogeneity. From the results, I confirmed that the endogeneity does not affect the results heavily. The results of the fourth and fifth robustness checks are in a technical appendix.

TABLE 15

ENDOGENOUS/INSTRUMENTAL VARIABLES' ROBUSTNESS

	(1)			(2)		
	Level	Full (DID)	Control (DID)	Level	Full (DID)	Control (DID)
Const	0.0870**	−0.0030	0.0013	0.0871**	−0.0026	0.0020
	(0.0022)	(0.0026)	(0.0067)	(0.0022)	(0.0026)	(0.0064)
Q_{it}, ΔQ_{it}	−0.0010	0.0038*	0.0048	−0.0005	0.0035	0.0048
	(0.0018)	(0.0023)	(0.0070)	(0.0018)	(0.0023)	(0.0067)
$\frac{CF_{i,t}}{K_{i,t-1}}$, $\Delta\frac{CF_{i,t}}{K_{i,t-1}}$	0.0422**	0.0345	0.0700	0.0403**	0.0334	0.0742
	(0.0134)	(0.0227)	(0.0494)	(0.0133)	(0.0227)	(0.0484)
Failure dummy	−0.0146*	−0.0203**	−0.0243**	−0.0148*	−0.0237**	−0.0290**
	(0.0082)	(0.0102)	(0.0113)	(0.0082)	(0.0102)	(0.0113)
J(p-value)	0.9478	0.8963	0.7443	0.7851	0.1828	0.5457
Endogeneity	Q_{it}	ΔQ_{it}		Q_{it}	ΔQ_{it}	
Instrument	$Q_{i,t-1}, Q_{i,t-2}, i_{it-1}$	$Q_{i,t-2}, Q_{i,t-3}, i_{it-2}$		$Q_{i,t-1}, Q_{i,t-2}, \frac{CF_{i,t-1}}{K_{i,t-2}}$	$Q_{i,t-2}, Q_{i,t-3}, \frac{CF_{i,t-2}}{K_{i,t-3}}$	

	(3)			(4)		
	Level	Full (DID)	Control (DID)	Level	Full (DID)	Control (DID)
Const	0.0872**	−0.0035	0.0027	0.0856**	−0.0043	0.0000
	(0.0022)	(0.0028)	(0.0069)	(0.0058)	(0.0029)	(0.0068)
Q_{it}, ΔQ_{it}	−0.007	0.0021	0.0073	−0.0012	0.0049	−0.0017
	(0.0018)	(0.0031)	(0.0087)	(0.0030)	(0.0023)	(0.0113)
$\frac{CF_{i,t}}{K_{i,t-1}}$, $\Delta\frac{CF_{i,t}}{K_{i,t-1}}$	0.0410**	0.0384*	0.0621	0.0603**	−0.0456	0.2247
	(0.0134)	(0.0236)	(0.0494)	(0.0709)	(0.0556)	(0.2027)
Failure dummy	−0.0148*	−0.0234**	−0.0274**	−0.0143*	−0.0199**	−0.0320**
	(0.0082)	(0.0102)	(0.0115)	(0.0084)	(0.0105)	(0.0135)
J(p-value)	0.8027	0.1421	0.0399	0.9162	0.1572	0.3402
Endogeneity	Q_{it}	ΔQ_{it}		$Q_{it}, \frac{CF_{i,t}}{K_{i,t-1}}$	$\Delta Q_{it}, \Delta\frac{CF_{i,t}}{K_{i,t-1}}$	
Instrument	Q_{it-1}, Q_{it-2}	$\Delta Q_{it-1}, \Delta Q_{it-2}$		$Q_{i,t-1}, Q_{i,t-2}, \frac{CF_{i,t-1}}{K_{i,t-2}}$	$Q_{i,t-2}, Q_{i,t-3}, \frac{CF_{i,t-2}}{K_{i,t-3}}$	

NOTES: **Significant at 5%. *Significant at 10%. The standard errors are in parentheses. Dependent variable is Δi_{it}. "Control" is the sample of firms whose bank health is in bottom 33%.

TABLE 16

ROBUSTNESS OF BANK-FAILURE DUMMY'S CONSTRUCTION

	(1) 95%			(2) 80%			(3) 65%		
	Level	Full (DID)	Control (DID)	Level	Full (DID)	Control (DID)	Level	Full (DID)	Control (DID)
Const	0.0881**	−0.0026	−0.0024	0.0872**	−0.0027	−0.0001	0.0871**	−0.0021	−0.0006
	(0.0022)	(0.0026)	(0.0070)	(0.0022)	(0.0026)	(0.0067)	(0.0022)	(0.0025)	(0.0059)
Q_{it}, ΔQ_{it}	−0.0016	0.0038*	−0.0020	−0.007	0.0037*	0.0024	−0.0009	0.0039	0.0038
	(0.0021)	(0.0022)	(0.0087)	(0.0018)	(0.0022)	(0.0072)	(0.0018)	(0.0024)	(0.0057)
$\frac{CF_{i,t}}{K_{i,t-1}}$, $\Delta \frac{CF_{i,t}}{K_{i,t-1}}$	0.0477**	0.0296	0.0586	0.0410**	0.0341	0.0741	0.0432**	0.0342	0.0473
	(0.0148)	(0.0220)	(0.0480)	(0.0134)	(0.0225)	(0.0502)	(0.0132)	(0.0226)	(0.0450)
Failure dummy	−0.0194**	−0.0187*	−0.0211*	−0.0148*	−0.0234**	−0.0270**	−0.0041	−0.0198*	−0.0199
	(0.0093)	(0.0108)	(0.0123)	(0.0082)	(0.0103)	(0.0114)	(0.0094)	(0.0122)	(0.0127)
J(p-value)	0.7581	0.4519	0.7559	0.8027	0.3870	0.4483	0.7664	0.4291	0.4066
Endogeneity	Q_{it}	ΔQ_{it}	ΔQ_{it}	Q_{it}	ΔQ_{it}	ΔQ_{it}	Q_{it}	ΔQ_{it}	ΔQ_{it}
Conditional heteroskedasticy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTES: **Significant at 5%. *Significant at 10%. The standard errors are in parentheses. Dependent variable is i_{it}(level) and Δi_{it}(DID). Instrument variables are $Q_{i,t-2}, Q_{i,t-3}$. "Control" is the sample of firms whose bank health is in bottom 33%.

TABLE 17

ROBUSTNESS OF CONTROL GROUP CONSTRUCTION

	(1) 10% Control (DID)	(2) 33% Control (DID)	(3) 50% Control (DID)
Const	−0.0002	−0.0001	−0.0051
	(0.0109)	(0.0067)	(0.0047)
ΔQ_{it}	−0.0199	0.0024	−0.0022
	(0.0232)	(0.0072)	(0.0060)
$\Delta \frac{CF_{i,t}}{K_{i,t-1}}$	0.1721*	0.0741	0.0118
	(0.1024)	(0.0502)	(0.0387)
Failure dummy	−0.0372*	−0.0270**	−0.0233**
	(0.0221)	(0.0114)	(0.0109)
J(p-value)	0.3034	0.4483	0.3876
Endogeneity	ΔQ_{it}	ΔQ_{it}	ΔQ_{it}
Conditional heteroskedasticy	Yes	Yes	Yes

NOTES: **Significant at 5%. *Significant at 10%. The standard errors are in parentheses. Dependent variable is Δi_{it}. Instrument variables are $Q_{i,t-2}$, $Q_{i,t-3}$. Bank/firms connection criteria are fixed in 80%.

6. CONCLUSION

Client firms' investments are severely affected by bank failures. Using an experimental set of unique nationwide bank failures and loan quantity data in the late 1990s in Japan, this study separately identifies the lending-market shock on firms due to bank failures. The main findings are the following. First, bank failures decrease the client firms' investments by around 30%. Therefore, as predicted by theory, I confirmed bank failures' effects on their client firms and clarified one avenue through which large bank failures can cause/amplify recessions. Second, the data suggest that potentially high investment growth/level firms choose/are chosen by unhealthy banks. Failing to account for this behavior causes a 30–80% lesser bias in ordinary level estimates. The results of this paper indicate that in a recession unhealthy banks allow their clients to invest at high rates to recover. Therefore, the bank failures' effect on client firms is greater than predicted in the previous literature, which does not address this selection behavior. Third, there is no evidence implying that the lack of other financial sources also produces the negative shocks. Rather, the financing cut itself due to bank failures, resulted in the decreased investments. This shows that in recessions, when the credit risk is higher, the relationship between banks and firms are crucial and firms cannot find alternative banks.

This paper has two policy implications. The effect of bank failure is larger than what the past literature had previously predicted. During a financial crisis, unhealthy banks tend to help high potential investment growth/level clients to resuscitate and/or high potential investment growth firms to choose unhealthy banks. Therefore, the bank failures will reduce the economic activity of these firms. We must consider these effects when we discuss bank failures' effects. For the client firms of unhealthy banks, whether their banks go bankrupt or not is of extreme significance, and true bank-failure shocks on client firms are very crucial. Second, the relationships between banks and firms are extremely influential. If banks stop lending to their client firms, the firms cannot find new financial sources during the recession and client firms are forced to decrease their investments by nearly 30%. This is because other banks may allocate their available funds to their own clients and debt/stock markets do not become alternate options. The use of governmental loans as substitutes for the clients of failed banks may be an effective solution to both prevent a recession from occurring or, if a recession has begun, prevent its amplification.

LITERATURE CITED

Ashcraft, Adam B. (2005) "Are Banks Really Special? New Evidence from the FDIC Induced Failure of Healthy Banks." *American Economic Review,* 95, 1712–30.

Bae, Kee-Hong, Jun-Koo Kang, and Chan-Woo Lim. (2002) "The Value of Durable Bank Relationships: Evidence from Korean Banking Shocks." *Journal of Financial Economics,* 64, 181–214.

Berger, Allen N., and Gregory Udell. (1994) "Did Risk-Based Capital Allocate Bank Credit and Cause a 'Credit Crunch' in the United States? " *Journal of Money, Credit, and Banking,* 26, 585–628.

Bernanke, Ben S. (1983) "Nonmonetary Effects of the Financial Crisis in the Propogation of the Great Depression." *American Economic Review,* 73, 257–76.

Bernanke, Ben S., and Cara S. Lown. (1991) "The Credit Crunch." *Brookings Papers on Economic Activity,* 2, 205–79.

Blundell, Richard, Stephen Bond, Michael Devereux, and Fabio Schiantarelli. (1992) "Investment and Tobin's Q." *Journal of Econometrics,* 51, 233–57.

Brewer, Elijah, III, Hesna Genay, William Curt Hunter, and George G. Kaufman. (2003) "The Value of Banking Relationship during a Financial Crisis: Evidence from Failures of Japanese Banks." *Journal of the Japanese and International Economics,* 17, 233–62.

Calomiris, Charles W., and Joseph R. Mason. (2003) "Consequences of Bank Distress During the Great Depression." *American Economic Review,* 93, 937–47.

Dehejia, Rajeev H., and Sadek Wahba. (1999) "Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs." *Journal of the American Statistical Association,* 94, 1053–62.

Dewatripont, Mathias, and Eric Maskin. (1995) "Credit and Efficiency in Centralized and Decentralized Economies." *Review of Economic Studies,* 62, 541–56.

Driscoll, John C. (2004) "Does Bank Lending Affect Output? Evidence from the U.S. States." *Journal of Monetary Economics,* 51, 451–71.

Fukuda, Shin-ichi, and Satoshi Koibuchi. (2006) "The Impacts of "Shock Therapy" under a Banking Crisis: Experience from Three Large Bank Failures in Japan." *Japanese Economic Reviews,* 57, 232–56.

Gibson, Michael S. (1995) "Can Bank Health Affect Investment? Evidence from Japan." *Journal of Business,* 68, 281–308.

Hayashi, Fumio. (1997) "The Main Bank System and Corporate Investment: An Empirical Reassessment." NBER Working Paper No. W6172.

Hayashi, Fumio, and Tohru Inoue. (1991) "The Relation between Firm Growth and Q with Multiple Capital Goods: Theory and Evidence from Panel Data on Japanese Firms." *Econometrica,* 59, 731–53.

Heckman, James, Hidehiko Ichimura, Jeffrey Smith, and Petra Todd. (1998) "Characterizing Selection Bias Using Experimental Data." *Econometrica,* 66, 1017–98.

Hoshi, Takeo, Anil Kashyap, and David Scharfstein. (1991) "Corporate Structure, Liquidity, and Investment: Evidence from Japanese Industrial Groups." *Quarterly Journal of Economics,* 106, 33–60.

Hosono, Kaoru, and Masaya Sakuragawa. (2003) "Soft Budget Constraint Problems in the Japanese Credit Market." Nagoya City University Discussion Papers in Economics, No. 345.

Imbens, Guido W., and Jeffrey M. Wooldridge. (2008) "Recent Developments in the Econometrics of Program Evaluation." NBER Working Paper No. 14251.

Mcguire, Patrick. (2001) "The Way to Construct Tobin's Q from DBJ Database." Unpublished manuscript.

Peek, Joe, and Eric S. Rosengren. (2000) "Collateral Damage: Effect of the Japanese Bank Crisis on Real Activity in the United States." *American Economic Review,* 90, 20–45.

Peek, Joe, and Eric S. Rosengren. (2005) "Unnatural Selection: Perverse Incentives and the Misallocation of Credit in Japan." *American Economic Review,* 95, 1144–66.

Petersen, Mitchell A., and Raghuram G.Rajan. (1995) "The Effect of Credit Market Competition on Lending Relationships." *Quarterly Journal of Economics,* 110, 407–43.

Rosenbaum, Paul R. (2002) *Observational Studies,* 2nd ed. New York: Springer.

Slovin, Myron B., Marie E. Sushka, John A. Polonchek. (1993) "The Value of Bank Durability: Borrowers as Bank Stakeholders." *Journal of Finance,* 48, 247–66.

Yamori, Nobuyoshi, and Akinobu Murakami. (1999) "Does Bank Relationship Have an Economic Value? The Effect of Main Bank Failure on Client Firms." *Economics Letters,* 65, 115–20.

Watanabe, Wako. (2007) "Prudential Regulation and the 'Credit Crunch': Evidence from Japan." *Journal of Money, Credit and Banking,* 39, 639–65.

Woo, David. (2003) "In Search for 'Capital Crunch': Supply Factors behind the Credit Slowdown in Japan." *Journal of Money, Credit and Banking,* 35, 1019–38.