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Essays in Banking and Monetary Policy

A dissertation submitted in partial satisfaction of the
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in

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by

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2017

The dissertation of Koji Takahashi is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

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2017

DEDICATION

This thesis is dedicated to my family: Sachiyo, Ryunosuke, Rintaro, Ran, Susumu, Kikuko, Sayoko, and Tomoji. Without their help, I could not have finished this thesis.

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Chapter 1, "The Real Effects of Bank-Driven Termination of Relationships: Evidence from Loan-Level Matched Data" in full, has been submitted for publication of the material as it may appear in Journal of Financial Stability. Kiyotaka Nakashima, and Koji Takahashi are the authors of this paper.

Chapter 2, "Risk-Taking Channel of Unconventional Monetary Policies in Bank Lending" in full, is currently being prepared for publication of the material. Masahiko Shibamoto, Kiyotaka Nakashima, and Koji Takahashi are the authors of this paper.

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ABSTRACT OF THE DISSERTATION

Essays in Banking and Monetary Policy

by

Koji Takahashi

Doctor of Philosophy in Economics

University of California, San Diego, 2017

Professor James Hamilton, Chair

Chapter 1 examines the effects of bank-driven terminations of bank-borrower relationships on the borrowers' investments by exploiting a matched dataset of Japanese banks and firms. I find that bank-driven terminations significantly decrease investment when the firms facing termination have difficulty in either establishing new relationships or increasing borrowings within their existing relationships. Such termination effects are larger than those due to credit reduction within continuing relationships and are more pronounced for smaller firms. Our findings coincide with previous literature emphasizing financial frictions in the matching process and the importance of relation-specific assets in credit markets.

Chapter 2 investigates the effects of unconventional monetary policy on bank lending, using a bank-firm matched dataset in Japan from 1999 to 2015 by

disentangling conventional and unconventional monetary policy shocks employed by the Bank of Japan over the past 15 years. I find that a rise in the share of the unconventional assets held by the Bank of Japan boosts lending to firms with a lower distance-to-default ratio from banks with a lower liquid assets ratio and higher risk appetite. In contrast to the composition shock, the monetary base shock of increasing the Bank of Japan's balance sheet size does not have heterogeneous effects on bank lending. Furthermore, we find that interest rate cuts stimulate lending to risky firms from banks with a higher leverage ratio.

Chapter 3 contributes to the debate about the the effect of bank loan supply shocks on real economy, using bank lending stance shocks derived from the industry-level Short-term Economic Survey of Enterprises (Tankan) survey data in Japan. The identified bank lending stance shocks enable us to investigate the effect of loan supply shocks on the real economy over the past 30 years in a consistent manner using a structural vector auto regressive model, thereby leading to three main conclusions. First, a negative bank loan supply shock, which means a tightening of banks' lending stance, significantly decreases real GDP growth rates. However, loan supply shocks were not main driving factors for fluctuations of the real economy; the contribution of bank loan supply shocks to GDP is less than 10%. Third, I find that the economy with a zero lower bound constraint is more vulnerable to an adverse loan supply shock compared to that without the constraint as predicted by existing theoretical models. In a zero lower bound environment, loan supply shocks contribute to approximately 10% of the GDP fluctuations.

Chapter 1

The Real Effects of Bank-Driven Termination of Relationships: Evidence from Loan-Level Matched Data

Of all recent financial crises in developed economies, the crisis in Japan in the 1990s following the collapse of the bubble economy was unprecedented in terms of the length and depth of the subsequent economic downturn. As shown in Figure 1.1, bank lending and private investment declined continuously from the early 1990s to the early 2000s. The existing literature on Japan's financial depression has already investigated the existence of a credit crunch during this period and its impact on firm investment.[1] During this period, however, not only did aggregate bank loans decrease but the number of relationship terminations between firms and their banks also increased, as shown in Figure 1.2 (see Section 1.2 for the definition of bank relationship termination).

[1]For instance, Woo (2003) and Watanabe (2007) used bank-level panel data to conclude that there was a credit crunch during the late 1990s. Conversely, using loan-level matched data, Peek and Rosengren (2005) found evidence that during the 1990s, Japanese banks with impaired capital instead provided more loans to distressed borrowing firms. For empirical studies in the US, see Bernanke and Lown (1991), Peek and Rosengren (1995), Berrospide and Edge (2010), and Carlson et al. (2013).

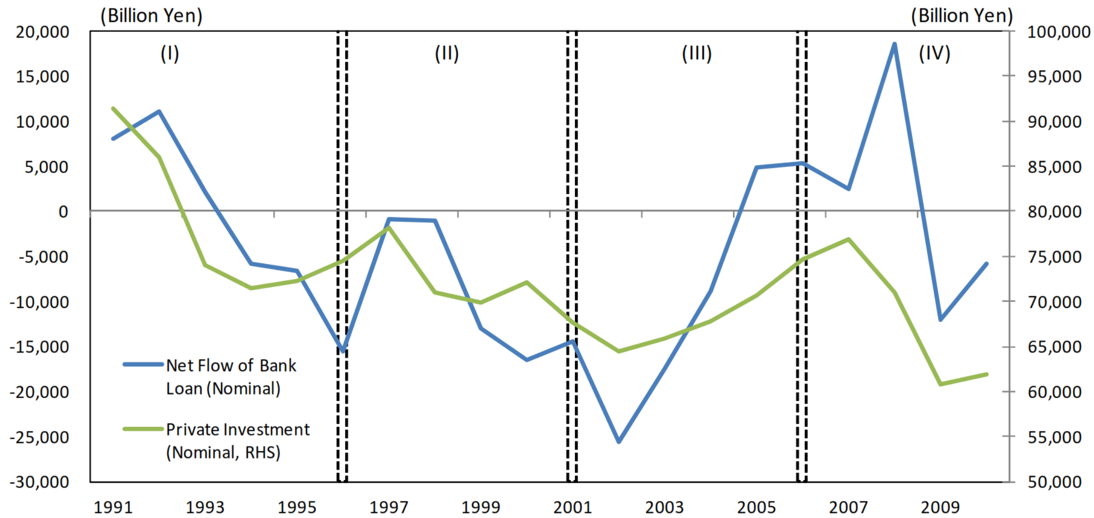


Figure 1.1: Bank Loans and Private Investment

Notes: The net flow of bank loans is the amount of bank loans that flow from private banks to non-financial private firms from the Flow of Funds. Private Investment is the gross nominal value of private domestic investment in GDP. A dotted vertical line indicates the starting year of each subsample period.

This paper empirically addresses the above coexistence of the increase in relationship terminations, and the decline in bank loans and firm investment by investigating whether and how these terminations due to the lender-side shocks affected firm investment behavior. Thus, we extend the premise of a "bank balance sheet channel," focusing on the relationship terminations as a mechanism that amplifies adverse economic shocks.[2]

For the most part, the extant literature has considered the role of the bank balance sheet channel from the perspective of firms or banks and not the relationships between them. This means that the literature does not explicitly distinguish between changes in bank loans resulting from terminating or maintaining exist-

[2]The theoretical literature about the balance sheet channel includes Bernanke and Gertler (1989), Holmström and Tirole (1997), Kiyotaki and Moore (1997), Bernanke et al. (1999), Diamond and Rajan (2005), and Gertler and Kiyotaki (2010). For the empirical literature that particularly focuses on a bank balance sheet's effect on a firm's investment and export behavior in Japan, see Gibson (1995; 1997), Kang and Stulz (2000), Chapter 4 in Ogawa (2003; 2007), Gan (2007a), and Amiti and Weinstein (2011; 2013). Of these, Gan (2007a) and Amiti and Weinstein (2011; 2013) employed bank-borrower matched data, whereas the remaining studies used firm-level panel data.

Figure 1.2: The Number of New Relationships and Termination

Notes: New Relation and Termination indicate sample averages that are calculated period-by-period using the numbers of new relationships and terminations, and are normalized by the number of listed firms. A dotted vertical line indicates the starting year of each subsample period.

ing relationships. However, when we consider the role of relationship banking in mitigating asymmetric information problems between banks and borrowing firms, which prior studies have investigated (see e.g. Hoshi et al. (1990), Petersen and Rajan (1995), and Boot (2000)), termination of a relationship has a more significant impact on firms' performance than a mere decrease in bank loans within continuing relationships, partly because search frictions exist in credit markets, and partly because termination destroys some relation-specific assets between banks and borrowing firms.

Given this insight, some recent theoretical studies, including Den Haan et al. (2003), Wasmer and Weil (2004), and Becsi et al. (2005; 2013), have proposed a mechanism for prolonging the effect of relationship terminations on the real sector from the perspective of matching lenders and borrowers in the credit market. In these theoretical frameworks, a credit expansion and firm investment cannot immediately react in response to a positive aggregate shock because it takes time to identify a profitable project because of frictions and asymmetric information in the credit market.[3] Meanwhile, a credit contraction that causes relationship terminations can occur immediately following a negative aggregate shock.[4]

The existence of a relation-specific asset between banks and borrowing firms is studied by Miyakawa (2010) and Nakashima and Takahashi (2017), using Japanese bank–firm matched data. They empirically demonstrated that a longer duration of bank–borrower relationships decreased the probability of termination and thus increased the value of the relation-specific asset, though the mechanism of termination and the value of the relationship-specific asset differ depending on the condition of credit markets (see Becsi et.al (2005; 2013) and Nakashima and Takahashi (2017)).

[3] As emphasized in the theoretical studies, the credit markets have as strong a claim to search frictions as do the labor markets. Commercial bank loans are complicated contracts requiring negotiations over the interest rate, fees, and covenants, with firms searching for the best deal. Conversely, banks search for profitable borrowers, make loan evaluations, and screen out likely losses.

[4] Dell'Ariccia and Garibaldi (2005) demonstrated empirically that a credit contraction is more volatile than a credit expansion within the US banking industry; in particular, they noted the search process was a driving factor in generating the asymmetric volatility of the credit.

According to the above studies, if firms face bank-driven terminations, these firms would decrease their investment because they expect that it will require time and that it will be costly to establish new relationships during the search process and to reconstruct relation-specific assets. From this viewpoint, the difference between the estimated impacts of relationship terminations and credit contractions within continuing relationships shows to what extent search frictions and the loss of relation-specific assets affect firms' performance after bank-driven terminations. Moreover, such impacts of relationship terminations depend on how severely firms that have experienced terminations face asymmetric information problems and whether these firms can immediately find an alternative funding source by establishing new borrowing relationships or increasing their borrowings within their existing banking relationship. We examine this prediction by exploiting the matching structure of our loan-level dataset.

Like ours, recently a few empirical studies have documented the importance of bank–borrower relationships in establishing the effect of credit undersupply on borrower outcomes (see e.g. Chava and Purnanandam (2011), Chodorow-Reich (2014), and Carvalho et al. (2015)); however, unlike ours, these studies have not focused on the dynamic borrowing and lending relationships between firms and banks following a negative credit supply shock. To our knowledge, ours is the first study to address the importance of banking relationships by focusing on the credit availability of firms facing bank-driven terminations and their asymmetric information problems in the credit market.

In this paper, we measure the effect of terminations on the real economy in terms of the bank balance sheet channel. However, there are some difficulties in establishing this causal effect empirically. The first arises because relationship terminations occur for many different reasons. For example, the lending bank may be unwilling to maintain the relationship with the firm, or the borrowing firm may wish to terminate the relationship with the bank, or both. The central challenge tackled by this paper is to disentangle the lender-driven relationship terminations from other reasons for termination using a bank–borrower-matched sample.[5] To isolate the bank-driven factors in relationship terminations, we use banks' predetermined variables that capture the soundness of their balance sheets as instrumental variables. Thus, we are able to measure the causal effect of the exogenous lender-side shock of termination on firm investment.

A second difficulty in examining bank-driven termination involves preparing a loan-level matched sample and identifying relationship termination. We prepare the matched sample for the period from 1991 through to 2010 in Japan. This contrasts with other studies of bank–borrower relationships in Japan, including Peek and Rosengren (2005), Gan (2007a), and Tsuruta (2014), which have employed matched samples only for the late 1990s. The difficulty in preparing the matched sample and identifying relationship terminations after the late 1990s is mainly because the Japanese banking sector was subject to extensive mergers and acquisitions (M&A) and divestiture activity throughout the late 1990s and into the early 2000s. Prior to our empirical analysis, we checked whether succeeding banks took over the credit claims of the eliminated or consolidated banks before and after the relevant M&As and divestitures. Thus, we constructed our matched sample for the period after the late 1990s.

By using the loan-level matched dataset, we find that banks with larger exposures to the real estate industry during the bubble economy of the late 1980s were more likely to terminate their relationships in the early 2000s, when Japanese banks were compelled to dispose of nonperforming loans and relatively important relationships for borrowing firms were terminated. Such bank-driven terminations had about a one-year lasting effect on firm investment and a decrease in bank loans caused by these terminations had a more significant effect on firm investment than a mere change of loans in continuing relationships. Therefore, relationship terminations matter per se.

We also show that the termination effects in the early 2000s can be attributed to firms' difficulties in immediately obtaining other sources of bank credit by switching to new relationships or increasing their borrowings within their ex-

[5]Tsuruta (2014) exploited firm changes in main banks over the 1990s in Japan and thus identified the borrower-driven effect of main-banking relationship terminations on firm performance, but not their lender-driven effect.

isting relationships. This mechanism for the bank-driven termination effect was more substantial for smaller firms facing severe asymmetric information problems, which is consistent with the implication of the theoretical and empirical literature documenting the importance of bank–borrower relationships.[6]

The remainder of the chapter is organized as follows. Section 1.1 discusses our loan-level matched dataset and proposes a method for the estimation of the bank-driven termination effect. Section 1.2 reports the estimation results for the termination effect on firm investment, and Section 1.3 explores the background mechanism. Section 1.4 extends the analysis of the bank-driven terminations by conducting a robustness check. Section 1.5 provides some concluding comments. The Appendix A explains how we define a relationship termination in the cases of M&A, business transfer, and divestiture.

1.1 Matched Data and the Estimation Method

In this section, we start by introducing a firm-level equation for the outcome variables, including firm investment, and then explain our loan-level matched dataset. We also describe an estimation method to identify the causal effect of bank-driven terminations on a firm's outcome variables.

1.1.1 Firm-level Equation for an Outcome Variable

To investigate the effect of relationship terminations on firms, we specify a firm-level equation for an outcome variable $y_{i,t}$ as follows:

$$y_{i,t} = a + b_y y_{i,t-1} + b_{cut}\mathrm{CUT}_{i,t} + \mathbf{b_f'FIRM_{i,t-1}} + \mathbf{b_d'D_t} + \epsilon_{i,t}, \tag{1.1}$$

[6]Our findings resemble those of Chodorow-Reich (2014), which showed that borrowers from weaker banks could not switch to healthier banks during the 2008–09 financial crisis; these financial frictions had more negative impacts on employment at smaller firms and those without access to public debt markets. Carvalho et al. (2015) found that investment cuts were associated with bank distress during this financial crisis and were more pronounced for firms with strong lending relationships with banks and those with severe asymmetric information problems.

where $\mathrm{CUT}_{i,t}$ indicates firm i's termination variable, which varies depending on the relationship terminations between the borrowing firm i and some of its lending banks, occurring in fiscal year t. $\mathbf{FIRM_{i,t-1}}$ indicates the borrower-side covariates that control for the firm's attributes and characteristics, including its financial condition, profitability, funding sources, and relationships with its lending banks, at the end of fiscal year $t-1$. $\mathbf{D_t}$ denotes a vector of year dummies. $\varepsilon_{i,t}$ is a stochastic error term.

The outcome variable for firm i, $y_{i,t}$, can include proxies for the firm's financial condition and profitability. Throughout this analysis, we pay special attention to the effects of the termination variable, $\mathrm{CUT}_{i,t}$, on firm investment because it is a driving force in short- and long-run macroeconomic output. The difficulty of quantifying the effect of the termination variable, b_{cut}, involves disentangling the lender-side shocks from the borrower-side shocks; in other words, an endogeneity problem arises if a borrowing firm takes the initiative of terminating its own bank relationships.[7]

1.1.2 Matched Data and Relationship Termination

The empirical analysis developed in this paper rests on a loan-level dataset comprising a matched sample of Japanese banks and their borrowing firms listed in Japan. We construct our loan-level data based on the Corporate Borrowings from Financial Institutions Database compiled by Nikkei Digital Media Inc. This database assembles information on the outstanding amounts of bank loans classified by maturity (long-term debt with a maturity of more than one year and short-term debt with a maturity of one year or less) and by each bank. The database includes some 350,000 observations, comprising more than 130 Japanese banks, 2,000 listed borrowing firms and 17,000 relationships for our sample period from the fiscal year 1991 to 2010 (see Table 1.1). We combined the Nikkei database with the financial statement data of the Japanese banks and their listed borrowing

[7]Note that there are also other cases in which an endogeneity problem arises. For example, if a bank terminated its relationship with a poorly performing firm because of the firm's increasing risk of insolvency, a simple OLS regression would generate an estimation bias.

firms, also compiled by Nikkei Digital Media Inc.[8]

Table 1.1: Number of Observations: Average per Year

	Full Sample	1991–1995	1996–2000	2001–2005	2006–2010
Firms	2,061	1,559	2,324	2,263	2,099
Banks	137	151	147	131	121
Relations	17,042	18,331	21,693	15,751	12,394

Notes: This table shows sample averages of the numbers of observations for borrowing firms, lending banks, and relationships, each calculated per year. "Full Sample" indicates the sample period from fiscal year 1991 to 2010.

To quantify the fluctuations in the investments of the borrowing firms resulting from the lender-driven termination of bank relationships, we start by identifying a terminated bank–borrower relationship. In this analysis, we define the termination of a relationship in fiscal year t as the case where firm i borrowed from bank j at the end of year $t-1$ but not at the end of year t.[9]

As discussed earlier, the Japanese banking sector experienced extensive M&A, business transfer, and divestiture activity from the late 1990s to the early 2000s. Consequently, some Japanese banks are missing from the original Nikkei database at the end of our sample period. Therefore, to identify properly a terminated bank–borrower relationship, we took into account these eliminations and consolidations of Japanese banks. In other words, we thoroughly scrutinized whether succeeding banks took over the credit claims of eliminated or consolidated banks on their borrowing firms before and after the relevant restructuring event. The Appendix A details how we define a terminated relationship in the cases of M&A, business transfer, and divestiture.

As for exits of some firms from our loan-level dataset in the middle of

[8] The fiscal year-end for Japanese banks is March 31, but this is not necessarily the case for the borrowing firms. When combining the Nikkei database with the financial statement data, we match bank-side information to borrower-side information in the same fiscal year.

[9] In a durable bank–borrower relationship, long-term loans may be more important in determining firm investment. From this viewpoint, we also define relationships as terminated if there are long-term borrowings at the end of year $t-1$, but not t, although this definition of termination does not necessarily mean "relationship termination" because, in nearly every case, there can be short-term borrowings at the end of year t, even if there are not long-term borrowings at this time. We find that this termination has a significantly negative impact on firm investment, with the almost same magnitude as that reported below.

our full-sample period, we cannot identify whether the relationships with the firm were post-exit terminated, as these datasets are only for listed firms.[10] Therefore, we adopt the strategy of dropping a firm's observation from our dataset in year t if the firm exited from the original data after year t. Thus, if a firm's last observation in the original dataset was in t, our adjusted sample includes the firm's observations until year $t-1$. While this strategy could lead to the underestimation of the real effects of relationship termination, as termination could induce a crucial consequence for the firm such as bankruptcy, it is plausible because it provides a more conservative estimate of any termination effects.

In addition to a terminated relationship, we identify "new relationships" and thereby examine whether borrowing firms that experienced bank-driven terminations were able to alleviate negative shocks on investment by establishing new relationships. We define a new relationship as the situation in which a new relationship is established or a terminated relationship is revived. We do not distinguish between these two cases. In other words, a new relationship in year t is simply defined as the case where firm i borrowed from bank j at the end of year t but had not borrowed from that bank at the end of year $t-1$.

Figure 1.2 illustrates the historical paths of the average number of new relationships and terminations for listed firms for each period. As shown, new relationships and terminations gradually increased from the middle of the 1990s until the early 2000s.

Based on the identified terminations, we define a termination variable, $\mathrm{CUT}_{i,t}$, to be included in the firm outcome equation (1). We define the termination variable as the rate of change in the bank borrowings caused by relationship termination as follows:

$$\mathrm{CUT}_{i,t} = -100 \times \frac{\sum_{j \in B_{i,t-1}} \mathrm{X}_{i,j,t-1}\delta_{i,j,t}}{\sum_{j \in B_{i,t-1}} \mathrm{X}_{i,j,t-1}}, \tag{1.2}$$

where $\mathrm{X}_{i,j,t-1}$ indicates the loan amount that firm i borrowed from bank j at the end of year $t-1$, and $\delta_{i,j,t}$ is a dummy variable that takes a value of one if firm i

[10] There are many possible reasons for firm exit from our sample, including bankruptcy, management buyout, termination of all the firm's relationships, etc.

borrowed from bank j at the end of year $t-1$ but not at the end of year t. $B_{i,t-1}$ is the set of banks lending to firm i at the end of year $t-1$. This termination variable has a value ranging from -100 to 0, with a larger negative value implying a greater negative contribution of relationship terminations to the firm's outstanding borrowings.

Figure 1.5 plots the historical path of the sample averages for the termination variable ($\mathrm{CUT}_{i,t}$) by period against the growth rate of aggregate bank loans. As shown, the rate of decrease in outstanding bank borrowings caused by relationship terminations appears to increase continuously after the early 1990s.

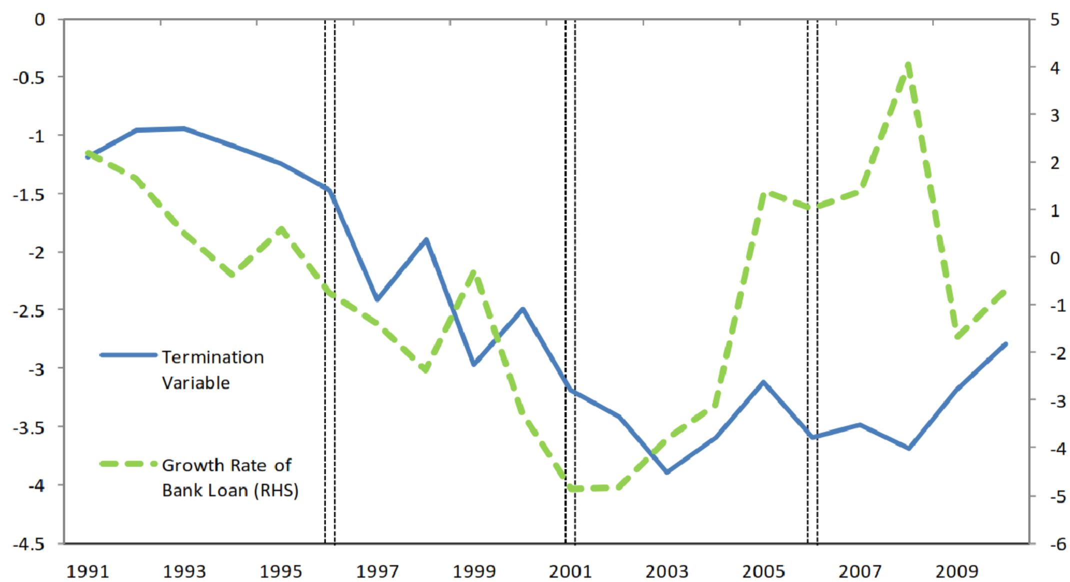


Figure 1.3: Termination Variable and the Growth Rate of Bank Loans

Notes: The historical path of the termination variable plots a sample average of the termination variable calculated at each period. The bank-loan growth rate is calculated as the chage rate of outstanding amount of bank loans from the Bank of Japan bank-lending survey and is shown in percentage terms. A dotted vertical line indicates a starting year of each subsample period.

1.1.3 Firm's Outcome Variable and Covariates

For the outcome variable $y_{i,t}$, we pay special attention to firm investment ($\mathrm{INVEST}_{i,t}$), as discussed in Section 1.1. We define the firm's investment as the first difference in log tangible fixed assets after adjusting for amortization, which is the growth rate in percentage terms.

To control for a firm's characteristics, we include nine attributes of the firm in the covariates $\mathbf{FIRM_{i,t-1}}$: the firm's book leverage ratio ($\mathrm{LEV}_{i,t-1}$), the liquidity ratio ($\mathrm{LIQUID}_{i,t-1}$), Tobin's q ($\mathrm{Q}_{i,t-1}$), the return on assets ($\mathrm{ROA}_{i,t-1}$), sales growth ($\mathrm{SALE}_{i,t-1}$), firm size ($\mathrm{SIZE}_{i,t-1}$), firm age ($\mathrm{AGE}_{i,t-1}$), the number of banks lending to firm i ($\mathrm{NUMBER}_{i,t-1}$), and a vector of industry dummy variables ($\mathbf{INDUSTRY}_i$) that indicates the industry to which borrowing firm i belongs.

We construct the leverage ratio and the liquidity ratio by dividing the book values of a firm's total debts and liquidity assets by its total assets, respectively. The leverage ratio and the liquidity ratio are in percentage terms. We include each financial ratio to control for a borrowing firm's ability to meet its financial obligations, assuming the leverage ratio and the liquidity ratio proxy for the firm's ability to meet its long- and short-term debt obligations, respectively.

Tobin's q is the ratio of the market value of firm i to its book value, where the market value of the borrowing firm is the market value of its equity plus the book value of its total liabilities.[11] The return on assets is the firm's net profits divided by the book value of its total assets. Sales growth is the growth rate of the firm's gross sales. We include Tobin's q to control for the firm's long-term profitability, while we use the return on assets and sales growth to control for the firm's short-term profitability.

We define firm age ($\mathrm{AGE}_{i,t-1}$) as the number of years that have elapsed up to the end of fiscal year $t-1$, or the number of years since a borrowing firm i started business. Firm size is the logarithm of the book value of its assets. The firm's number of relationships is the logarithm of the number of firm i's relationships with banks. We include the number of relationships to control for the intensity of the bank–borrower relationships. The industry dummy variables are set up according to the 33 industry sectors defined by the Securities Identification Code Committee (SICC) in Japan.

In addition to the nine borrower-side factors, we include those funding

[11] We calculate the market value of equity by multiplying the end-of-year stock price by the number of shares. Firm book value is the book value of total assets.

source variables that indicate the dependence of a firm's external funding on alternative sources other than bank loans, such as equities and corporate bonds. This is because we predict that a firm's funding dependence on each external funding source should affect both its relationships with lending banks and its investment behavior.[12] In our analysis, we consider three alternative funding sources to bank loans: equity, corporate bonds, and commercial paper. For the increase in equity of borrowing firm i, we specify an increase in equity dummy variable ($\mathrm{EQUITY}_{i,t-1}$), which takes a value of one if the number of issued stocks increases in fiscal year $t-1$. For the remaining two sources, we calculate the variations in the total amount of issues over the previous year, normalized by the firm's book value of total liabilities, to prepare two additional funding variables; namely, corporate bonds ($\mathrm{CB}_{i,t-1}$) and commercial paper ($\mathrm{CP}_{i,t-1}$). Corporate bonds include both straight and convertible bonds.

Table 1.2 provides descriptive statistics for each covariate. As shown, the mean firm leverage ratio (LEV) decreased continuously from 1991 to 2010. For funding sources, the number of relationships (NUMBER) exhibited a downward trend after 1991. The equity variable (EQUITY) decreased gradually through the early 2000s but recovered somewhat in the second half of the 2000s. The corporate bond ratio (CB) decreased sharply in the second half of the 1990s and remained negative over the sample period. Given that the termination variable (CUT) and the firm-leverage ratio (LEV) decreased continuously, the listed firms may have opted for deleveraging continuously.

[12]Leary (2009) exploited the US experience of two changes in bank-funding constraints–the 1961 emergence of the market for certificates of deposit and the 1966 credit crunch–thereby demonstrating that the changes in the composition of financing sources affected the role of bank lending support and thus firm capital structure choices. Uchino (2013) utilized Japan's experience during the 2008 financial crisis, thus demonstrating that firms with large holdings of corporate bonds that matured in 2008 increased bank borrowings to finance firm investment.

Table 1.2: Summary Statistics

	Full Sample				1991–1995		1996–2000		2001–2005		2006–2010	
	Mean	**Std.**	**Min.**	**Max.**	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
Termination Variable												
CUT	-2.617	8.926	-99.27	0.000	-1.087	5.417	-2.256	7.559	-3.427	10.45	-3.284	10.36
Firm Outcome												
INVEST	2.746	23.29	-858.6	543.7	5.900	14.74	3.421	14.30	0.420	23.91	2.050	33.33
Instrumental Variables												
$\text{WEXP}^{\text{E}state}$	11.27	1.883	0.000	24.56	11.66	1.662	11.30	1.645	11.17	1.921	11.05	2.183
WLEV	96.41	1.012	87.26	149.1	96.85	0.372	96.67	1.012	96.42	1.021	95.78	1.012
Firm Covariates												
LEV	60.20	19.41	0.91	835.4	64.05	17.84	61.36	19.87	59.90	20.47	56.38	18.11
LIQUID	51.05	19.67	0.60	99.37	56.65	18.14	53.43	18.86	48.70	19.65	46.18	20.35
Tobin's q	180.1	66.11	20.76	2537	208.8	51.34	179.1	61.62	167.9	65.91	172.4	74.11
ROA	0.572	7.781	-372.9	157.2	1.112	4.331	0.597	6.412	0.364	8.608	0.386	9.902
SALE	0.000	0.254	-4.689	7.305	0.010	0.170	0.019	0.174	0.022	0.278	-0.022	0.342
SIZE	10.48	1.441	4.522	16.46	10.98	1.382	10.52	1.391	10.29	1.422	10.26	1.481
AGE	3.792	0.575	-0.695	4.862	3.893	0.347	3.803	0.460	3.762	0.616	3.732	0.741

Table 1.2: Summary Statistics (continued)

	Full Sample				**1991–1995**		**1996–2000**		**2001–2005**		**2006–2010**	
	Mean	**Std.**	**Min.**	**Max.**	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
Firm Covariates												
NUMBER	1.882	0.699	0.000	4.560	2.243	0.695	2.019	0.668	1.754	0.629	1.591	0.623
EQUITY	0.263	0.441	0.000	1.000	0.399	0.492	0.272	0.441	0.198	0.395	0.222	0.419
CB	-0.282	6.719	-75.41	78.43	0.303	8.351	-0.753	7.328	-0.247	5.725	-0.263	5.442
CP	0.013	1.087	-32.03	26.25	0.050	0.793	0.012	1.247	-0.019	1.064	0.000	1.121
New Relationships												
MARRY	0.245	0.424	0.000	1.000	0.213	0.412	0.200	0.403	0.265	0.442	0.271	0.452

Note: Except for firm size (SIZE), firm age (AGE), the equity increase (EQUITY), firm sales growth (SALE), and the number of relationships (NUMBER), all variables are expressed in percentage terms.

1.1.4 Estimation Method

We use the instrumental variables method to disentangle supply shocks from demand shocks in relationship terminations by exploiting the turmoil that occurred in the real estate market and the capital crunches faced by banks in Japan following the collapse of the bubble economy.

The bursting of the Japanese bubble economy in the early 1990s severely damaged the capital positions of Japanese banks. Accordingly, some researchers have studied the lending behavior of these capital-impaired Japanese banks. Among these, Woo (2003) and Watanabe (2007) empirically demonstrated evidence of a bank credit crunch in the late 1990s. Here, impaired bank capital impeded bank lending regardless of whether the borrowing firms themselves were distressed. In contrast, Peek and Rosengren (2005) showed that capital-impaired Japanese banks, in fact, increased their loans to distressed borrowing firms during the 1990s because of window-dressing accounting motives.

Despite the differing implications of the effect of impaired capital for Japanese banks on their lending behavior, these studies share a common premise that impaired banks will change their lending attitudes toward their borrowing firms. Thus, the next question to be studied in the literature is why the "quality" of Japanese bank capital was impaired. Put differently, why did the nonperforming loans of banks increase after the bursting of the bubble economy in the early 1990s?

Ueda (2000), Hoshi (2001), and Ogawa (2003, Chapters 1 and 2) examined Japanese bank lending behavior over the period from the mid to the late 1980s. These studies demonstrated empirically that Japanese banks decreased loans to the manufacturing industry. However, they also indicate that banks increased loans to the real estate industry amid the rapid progression of financial deregulation and continuous increases in land prices during that period. The suggestion is that the shift in bank lending to the real estate industry resulted in an increase in the number of nonperforming loans after the bursting of the land price bubble and that this caused severe damage to the capital of Japanese banks.[13]

[13]Ueda (2000) and Hoshi (2001) found that increases in the number of loans to the real estate industry contributed to the increase in the number of nonperforming loans. Ogawa (2003, Chapters 1 and 2) showed that increases in the number of loans to small- and medium-sized business

Gan (2007a) and Watanabe (2007) exploited these findings to identify the causal effect of impaired capital for banks on their lending and borrowing firm investment for a period from the mid to the late 1990s. Both studies utilized the exposure of Japanese banks to the real estate industry during the late 1980s as an instrumental variable determining the quality of bank capital, thereby attempting to separate the impact of loan supply and loan demand shocks. One promising extension of their instrumental variable estimation method would be to use the exposure of banks to the real estate industry in the late 1980s as an instrumental variable for our termination variable (1) in order to isolate the lender-side shock in relationship terminations. To construct the instrumental variable, we first calculate the exposure of bank j to the real estate industry in fiscal year 1989, according to the following equation:

$$\mathrm{EXP}_{j,89}^{Estate} = 100 \times \frac{\text{Loans to Real Estate}_{j,1989}}{\text{Total Amount of Loans}_{j,1989}}, \tag{1.3}$$

where "Loans to Real Estate$_{j,1989}$" indicates bank j's outstanding loans to the real estate industry at the beginning of fiscal year 1989. "Total Amount of Loans$_{j,1989}$" denotes the total amount of bank j's outstanding loans at the beginning of fiscal year 1989.

Note that a firm outcome model is specified at the firm level, to examine the fluctuations in firm's outcome variables that are caused by lender-driven relationship terminations, as expressed in equation (1). This requires us to aggregate the lender-side information for each firm, including the exposure of the bank to the real estate industry. To aggregate the lender-side factors, we assume that the effect of a bank's capital condition on the borrowing firm is proportional to the firm's dependence on each bank. Given this assumption, we calculate the weighted average of the lender-side variables, using firm i's borrowing exposure to bank j in fiscal year $t-1$ defined as:

$$w_{i,j,t-1} = \frac{\mathrm{X}_{i,j,t-1}}{\sum_{j \in B_{i,t-1}} \mathrm{X}_{i,j,t-1}}, \tag{1.4}$$

enterprises, to the construction industry, to the finance and insurance industry, and to the real estate industry were largely responsible for the increase in nonperforming loans.

where $X_{i,j,t-1}$ is firm i's outstanding borrowings from bank j in fiscal year $t-1$, and $B_{i,t-1}$ is the set of banks that lend to firm i in fiscal year $t-1$.

Using this weighting, we then create an instrumental variable for the termination variable (2) as expressed by the weighted average of each bank's exposure to the real estate industry in 1989:

$$\mathrm{WEXP}_{i,t}^{Estate} = \sum_{j \in B_{i,t-1}} w_{i,j,t-1} \times \mathrm{EXP}_{j,89}^{Estate}. \tag{1.5}$$

This instrument would be valid if the variation in the bank's exposure to the real estate industry, across firms in 1989, was uncorrelated with the demand shocks that took place in the 1990s and 2000s. This assumption would be reasonable as long as we controlled fully for other factors such as the variations across industries. However, we can also argue that firms that were borrowing from banks with a higher exposure to the real estate industry in 1989 were more vulnerable to the demand shocks of the 1990s and 2000s. In Subsection 1.2.4, we discuss the validity (or orthogonality) and exclusion restriction of the instruments in a more rigorous statistical manner.

If we regard the past bank exposure to the real estate industry as a proxy for the "quality" of bank capital, another candidate for an instrument of the termination variable ($\mathrm{CUT}_{i,t}$) is the "quantity" of bank capital. Given that Japanese banks struggled to meet their regulatory capital requirements in response to the gradual decline in land and stock prices from the early 1990s to the late 1990s (see Fukao (2003) and Hoshi and Kashyap (2004; 2010)), a past value of the bank's capital position is one of the most promising instruments for the termination variable and indeed has been used in empirical studies to identify a credit undersupply following a bank balance sheet shock (e.g. Peek and Rosengren (1995; 2000), Calomiris and Wilson (2004), Carlson et al. (2013), and Nakashima and Takahashi (2017)). Hence, we adopt the one-period lag of the book leverage ratio of lending bank j, $\mathrm{BANKLEV}_{j,t-1}$, as a proxy for the "quantity" of bank capital. We then prepare the following second instrument as the weighted average of each bank's leverage ratio:

$$\text{WLEV}_{i,t} = \sum_{j \in B_{i,t-1}} w_{i,j,t-1} \times \text{BANKLEV}_{j,t-1}, \tag{1.6}$$

where the book leverage ratio of the lending banks ($\text{BANKLEV}_{j,t-1}$) is constructed in the same way as that of the borrowing firms ($\text{LEV}_{i,t-1}$) defined in the previous subsection. In the following analysis, we utilize both instruments, $\text{WEXP}_{i,t}^{Estate}$ and $\text{WLEV}_{i,t}$, thereby measuring the causal effect of bank-driven terminations on firm investment.[14]

Table 1.2 provides descriptive statistics for the two instruments. To avoid estimation bias arising from the correlation between the loan demand shocks and the bank instrument variables, we excluded firms in the four finance- and insurance-related sectors.[15]

We conduct two types of estimations using the two instrumental variables, $\text{WEXP}_{i,t}^{Estate}$ and $\text{WLEV}_{i,t}$. The first is a simple model without firm fixed effects, as shown in equation (1), and estimated by pooling the dataset. The second is a dynamic panel data model with firm fixed effects. If Japanese banks with impaired capital and greater exposure to the real estate industry have loaned to firms that are more vulnerable to demand shocks and the firms' vulnerability is not captured by observables, our two instrumental variables could correlate with the borrower-side unobservable factors. This correlation might result in the overestimation of the effect of relationship terminations on firm investment. Therefore, we also use the dynamic panel specification incorporating firm fixed effects as the output model (1), thereby controlling for firms' unobserved factors in the firm investment equation.[16]

For estimation of the dynamic panel model, we employ the generalized

[14]We do not use the regulated capital ratios and nonperforming loans as instrumental variables, because the definition of each variable differs markedly over time.

[15]Our dataset includes firms in 29 different sectors after excluding the following finance and insurance sectors: banks, securities and commodity futures, insurance, and other financing business industry.

[16]As discussed in the next section, we employ a five-year window for the estimation of the dynamic panel regression. Including the firm fixed effects in this short time window enables us to partially control for time-varying firm fixed effects.

method of moments estimation suggested by Arellano and Bond (1991). In Subsection 1.4.4, we show that the sorting effects of relationship terminations do not affect our results of the dynamic panel regression.

1.2 Estimation Results

This section reports the estimation results obtained by employing the instrumental variable method.

1.2.1 Rolling Estimation

Theoretical models that contain a matching structure in a credit market (Den Haan et al. (2003), Wasmer and Weil (2004), and Becsi et al. (2005; 2013)) and duration analyses of bank–borrower relationships (Miyakawa (2010) and Nakashima and Takahashi (2017)) suggest that credit market conditions could change the termination mechanism and its effects on the real economy. In order to incorporate this into our estimation of the firm outcome equation (1), we start by estimating a rolling regression over a five-year window and then identify subsample periods in which the termination mechanism and its effects differ substantially.

In our estimation with a pooled sample, the first-stage instrumental variable regression for the termination variable ($\mathrm{CUT}_{i,t}$) is specified as follows:

$$\mathrm{CUT}_{i,t} = a^* + b_y^* y_{i,t-1} + \mathbf{b_{IV}^{*'}IV_{i,t}} + \mathbf{b_f^{*'}FIRM_{i,t-1}} + \mathbf{b_d^{*'}D_t} + e_{i,t}, \tag{1.7}$$

where $\mathbf{IV_{i,t}}$ denotes a 2×1 vector of our instrumental variables, being the two proxies for the bank's capital condition, $\mathrm{WEXP}_{i,t}^{Estate}$ and $\mathrm{WLEV}_{i,t}$. For the second-stage regression, we specify the firm's outcome equation (1) including firm investment ($\mathrm{INVEST}_{i,t}$) as a dependent variable $y_{i,t}$. Below we report estimates of the coefficients $\mathbf{b_{IV}^*}$ on the two instrumental variables in the first stage, and the coefficient b_{cut} on the variable $\mathrm{CUT}_{i,t}$ in the second stage. By doing so, we explore periods during which the termination mechanism and its effect on firm investment have changed.

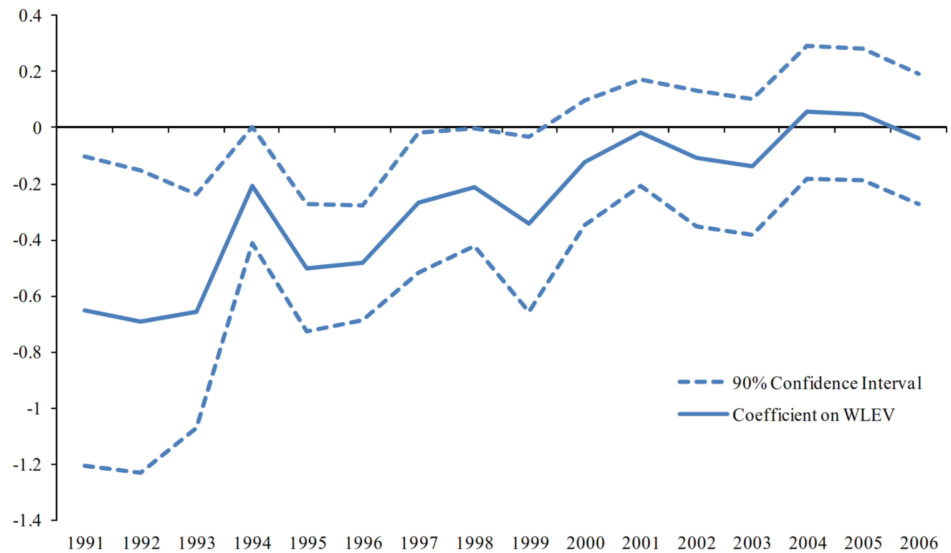
Figure 1.4 details the estimated coefficients for the two instrumental variables $\mathrm{WEXP}_{i,t}^{Estate}$ and $\mathrm{WLEV}_{i,t}$ in the first-stage regression (7). The solid line plots the point estimates based on the five-year subsample from year t through to $t+4$, and the dotted line indicates the 90% confidence interval for each estimate. The estimated coefficients in this figure provide an overview of the possible changes in the relationship termination mechanism in the Japanese bank loan market. The estimated coefficients for both of the instruments are negative in almost all periods, implying that a bank with greater exposure to the real estate industry and a higher leverage ratio is associated with larger decreases in bank loans because of relationship terminations. However, the two instruments illustrate a clear contrast between the 1990s and the 2000s. In the 1990s, the bank leverage ratio ($\mathrm{WLEV}_{i,t}$) affected the termination variable more significantly, whereas in the early 2000s, it was the bank exposure to the real estate industry ($\mathrm{WEXP}_{i,t}^{Estate}$).[17]

Figure **??** plots the estimated coefficients for the termination variable $\mathrm{CUT}_{i,t}$ obtained in the second-stage regression (1). From this figure, we can see that the estimated coefficients are negative in the early 1990s, albeit not significantly. Furthermore, the estimated coefficients start increasing from the late 1990s and are clearly positive by the early 2000s. However, as the confidence intervals become wider in the late 2000s, the estimated coefficients are statistically insignificant in this period.

The rolling estimation results reported in Figures 1.4 and 5 imply that the termination mechanism and its effect on firm investment change over time, particularly in the late 1990s and the early 2000s. To examine further the reasons for these changes, we divide our matched sample into four different subsample periods based on the above results and consider three other important macro variables relating to the Japanese bank loan market; namely, the growth rate of aggregate bank loans, the average number of terminations, and the termination variable (CUT). The four-subsample periods consist of period I, from fiscal year 1991 to 1995; period II, from 1996 to 2000; period III, from 2001 to 2005; and period IV, from 2006 to

[17] To consider these differences in the estimation results between the 1990s and the early 2000s, Section 1.3 discusses the difference in the financial situation of Japanese banks in the two sample periods.

WLEV



WEXP^{Estate}

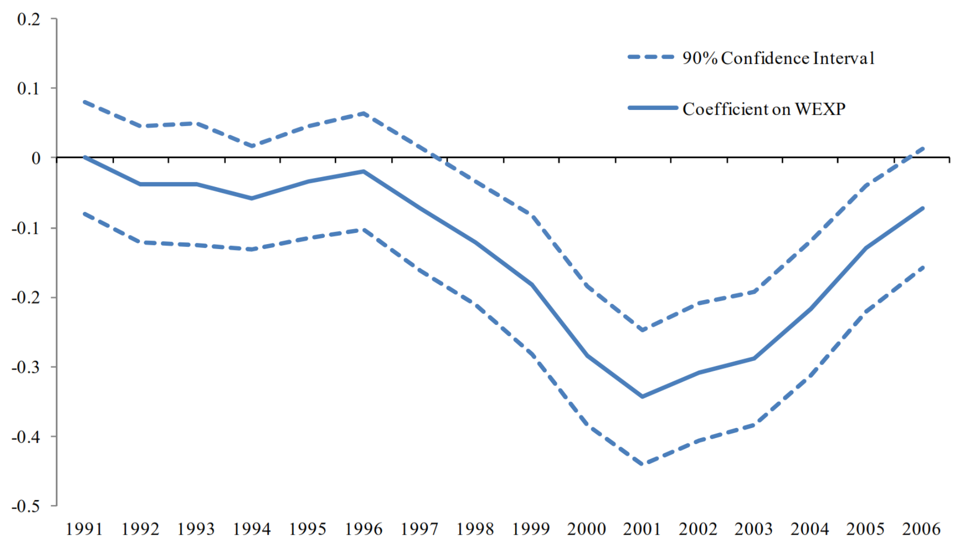


Figure 1.4: Estimated Coefficients on the Instruments in Rolling Window Estimations

Notes: The solid lines indicate the point estimates of the coefficients on the book leverage ratio (top) and the weighted exposure to the real estate industry (bottom) of banks, based on the 5-year rolling window estimation in the first stage regression. The X-axis indicates a starting year of each subsample period: A plot in year t shows an estimate based on the subsample period from year t through t+4.

2010. Each of these subsample periods well illustrates different developments in Japanese credit market conditions, as shown in Figures 1.2 and 1.5.

The first period from 1991 to 1995 corresponds with the time immediately after the collapse of the bubble economy, as stock and land prices peaked in 1989 and 1990, respectively (see Hoshi and Kashyap (2004)). During this period, although asset prices continued to decline, the aggregate growth rates of bank loans remained positive or around zero (see Figure 1.5). Furthermore, as shown in Figures 1.2 and 1.5, the increase in relationship terminations was relatively moderate: the average number of terminations for each firm was approximately 0.35, and the termination variable ($\mathrm{CUT}_{i,t}$) fluctuated around -1.

The second period from 1996 to 2000 is characterized by the beginning of the decrease in aggregate bank loans and the increase in relationship terminations. During this time, Japan's bank loan market began to contract clearly: as shown in Figures 1.2 and 1.5, aggregate bank loans decreased by approximately -1.5%, the average number of relationship terminations spiked at around 1 in 1999, and the termination variable decreased from -1.5 to -3. After this, the attitude of the Japanese government and regulatory authorities toward Japanese banks changed, which was probably one of the reasons for the shrinking of the bank loan market. In Section 1.3, we discuss in detail some regulation changes that affected Japanese bank behavior from the late 1990s and the early 2000s.

The third period is distinct from the earlier two periods in that the Japanese bank loan market contracted significantly: the aggregate growth rates of bank loans decreased to approximately -5%, as shown in Figure 1.5. In addition, as shown in Figures 1.2 and 1.5, the average number of terminations remained high at around 0.6, and the termination variable continued to decrease to -3.5 or less. Also note that as discussed later in Subsection 1.3.1, more important relationships for borrowing firms were terminated in the third period than in the second one.

The final period of the late 2000s includes a period of boom as well as the turmoil of the 2008 financial crisis. However, as shown in Figure 1.5, the aggregate growth rate of bank loans during this period remained relatively high, at least when compared with that in periods II and III. In addition, the termination variable began to increase to around -2 in the pre- and post-turmoil periods.[18]

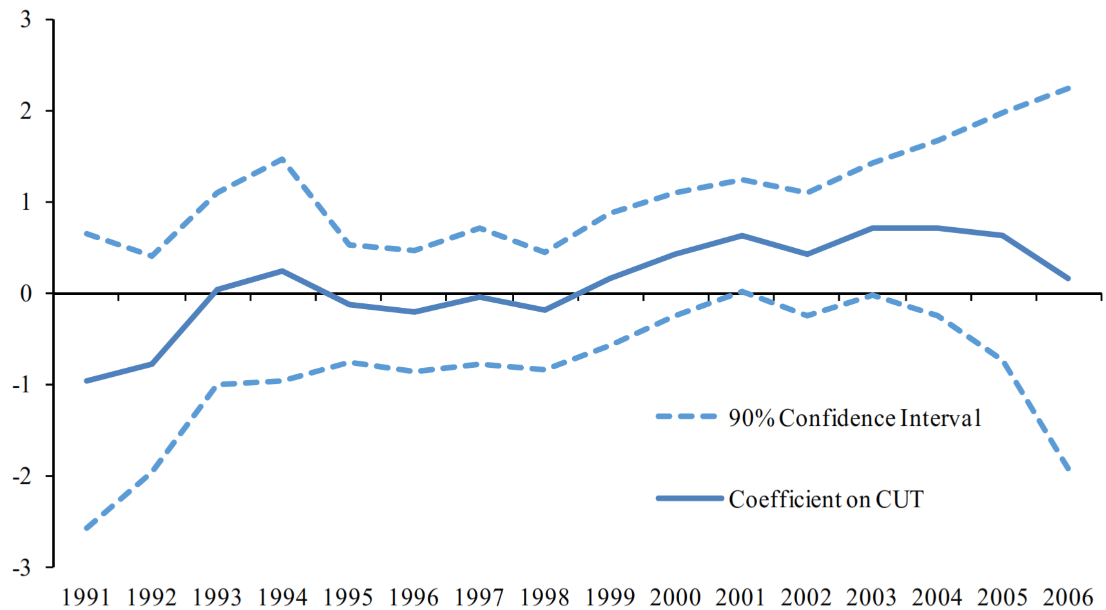


Figure 1.5: Estimated Coefficient on the Termination Variable in Rolling Window Estimations

Notes: The solid line indicates a point estimate of the coefficient on the termination variable, CUT, based on the 5-year rolling window estimation. The parameters are estimated by using the two instrumental variables with a pooled sample. The X-axis indicates a starting year of each subsample period: A plot in year t shows an estimate based on the subsample period from year t through t+4.

In the remainder of the paper, for the sake of simplicity, we focus on the estimation results from these four subsample periods instead of the rolling estimates in order to provide more detailed analysis of the relationship terminations.[19]

1.2.2 Estimation Results for Termination

Table 1.3 details the estimated coefficients for each subsample period from the first-stage regression for the pooled-sample model (7), as introduced in the

[18] Uchino (2013) pointed out that Japanese banks that had so far improved their capital condition remained financially sound and thus retained their financial intermediation function in response to firm funds demand amid the turmoil of the 2008 financial crisis.

[19] Conducting rolling estimations does not change our main conclusion from that derived from the four-subsample analysis.

previous subsection. Below we report the estimated coefficients, not only in order to examine the relevance of our two instruments ($\mathrm{WEXP}_{i,t}^{Estate}$ and $\mathrm{WLEV}_{i,t}$) for the termination variable but also to show how a firm's characteristics are associated with relationship terminations.[20]

In terms of the estimated coefficients for our instrumental variables, bank exposure to the real estate industry during the land price boom of the late 1980s ($\mathrm{WEXP}_{i,t}^{Estate}$) has a significantly negative estimate in period III of the early 2000s. On the other hand, the bank book leverage ratio ($\mathrm{WLEV}_{i,t}$) yields a significantly negative estimate for periods I and II of the overall period of the 1990s. These results imply that banks that had increased loans to the real estate industry during the land price boom of the late 1980s were more likely to terminate relationships with their borrowing firms during the early 2000s, while banks with less capital were more likely to do this during the 1990s. In Section 1.3, we suggest that this difference in estimation results may be attributable to the differing financial situation of Japanese banks in the two periods.

As for the relevance of our instrumental variables to the termination variable, we conducted a F test for weak instruments. Table 1.3 reports the F statistics for the null hypothesis that the instrumental variables are weak, based on the critical values presented by Stock and Yogo (2005). In subsample periods II and III, our instrumental variable estimations do not suffer from the problem of weak instruments because the null hypothesis is rejected at the desired maximal sizes of 25% and 10%, respectively. On the other hand, in subsample periods I and IV, the null hypothesis is not rejected. The effect of the bank variables on relationship terminations in periods I and IV is smaller as expected, given the fact that in these periods Japanese banks were not suffered from the problems of non-performing loans and the low capital as much as periods III and IV, as discussed in Woo (2003) and Uchino (2013). Because our interest is in the effects of bank-driven terminations, we focus on periods II and III in the following analyses. We should

[20]Miyakawa (2010) and Nakashima and Takahashi (2017) explored the reason for relationship terminations using a matched dataset for Japanese lending banks and listed firms. Ongena and Smith (2001) and Farinha and Santos (2002) used Norwegian and Portuguese bank–borrower matched data to examine the effect of the duration of bank–borrower relationships on relationship terminations.

Table 1.3: Estimation Results for the Relationship Termination Equation

Period	(I)	(II)	(III)	(IV)
	1991–1995	1996–2000	2001–2005	2006–2010
Dependent variable: CUT				
Independent variables:				
$WEXP^{Estate}$	0.0002	-0.020	-0.347***	-0.055
	(0.0489)	(0.051)	(0.059)	(0.053)
WLEV	-0.654*	-0.482***	-0.0064	-0.029
	(0.335)	(0.123)	(0.113)	(0.141)
Lag INVEST	0.0003	0.022*	-0.0001	0.005
	(0.0026)	(0.013)	(0.0081)	(0.006)
LEV	0.014***	0.029***	0.049***	0.038***
	(0.005)	(0.006)	(0.009)	(0.008)
LIQUID	-0.024***	-0.020***	-0.020**	-0.014*
	(0.005)	(0.006)	(0.008)	(0.008)
Q	-0.002	-0.005**	-0.009***	-0.006**
	(0.002)	(0.002)	(0.002)	(0.003)
ROA	0.013	0.047	0.107***	0.087***
	(0.013)	(0.033)	(0.031)	(0.025)
SALE	0.276	0.272	-0.246	0.691
	(0.278)	(0.480)	(0.534)	(0.578)
SIZE	-0.071	-0.193***	-0.201*	-0.218**
	(0.060)	(0.0703)	(0.107)	(0.106)
AGE	0.992***	0.119	1.250***	1.191***
	(0.254)	(0.209)	(0.305)	(0.259)

Table 1.3: Estimation Results for the Relationship Termination Equation (continued)

Period	(I)	(II)	(III)	(IV)
	1991–1995	1996–2000	2001–2005	2006–2010
Dependent variable: CUT				
Independent variables:				
NUMBER	0.185	-0.300*	-0.416**	-1.481***
	(0.126)	(0.161)	(0.200)	(0.222)
EQUITY	-0.073	-0.426**	-0.886***	-1.462***
	(0.145)	(0.188)	(0.323)	(0.340)
CB	-0.012	-0.038***	0.023	-0.005
	(0.009)	(0.011)	(0.022)	(0.040)
CP	0.013	0.148***	0.056	0.081
	(0.032)	(0.057)	(0.112)	(0.123)
Dummy	Year and Ind.	Year and Ind.	Year and Ind.	Year and Ind.
N	7510	10322	10365	9551
F-stat	2.09	$8.57^{\dagger}$	$20.50^{\ddagger}$	1.11

Notes: We conducted an ordinary least squares estimation for termination equation (7) by including year and industry dummy variables. Robust standard errors are in parentheses.*, ** and *** indicate 10%, 5% and 1% levels of significance, respectively. † and ‡ indicate a 5% level of significance based on the critical values at sizes 25% and 10%, respectively, as reported in Stock and Yogo (2005).

note that at least in periods I and IV, we cannot correctly estimate the effect of lender-driven terminations.

Regarding the estimation results for the firm characteristics, the one-period lag of firm investment ($\mathrm{INVEST}_{i,t-1}$) has a significantly positive estimate only for period II. This positive estimate implies that an increase in firm investment led to it maintaining its existing relationships, thus reducing the decrease in bank borrowings caused by the termination of its bank–borrower relationships.

The firm covariates of $\mathbf{FIRM_{i,t-1}}$, being the book leverage ratio ($\mathrm{LEV}_{i,t-1}$), the return on assets ($\mathrm{ROA}_{i,t-1}$), and firm age ($\mathrm{AGE}_{i,t-1}$) all display significantly positive estimates. These indicate that a highly leveraged and currently profitable firm of advanced age is associated with a smaller rate of decrease in its termination-related bank borrowings. In other words, such a firm has a greater tendency to maintain its existing bank–borrower relationships.

On the other hand, the liquidity ratio ($\mathrm{LIQUID}_{i,t-1}$), Tobin's q ($\mathrm{Q}_{i,t-1}$), and firm size ($\mathrm{SIZE}_{i,t-1}$) provide significantly negative estimates. The negative estimates for these variables indicate that a smaller firm holding less liquid assets with diminished future profitability is more likely to maintain its bank–borrower relationships.

For the number of firm relationships with its banks ($\mathrm{NUMBER}_{i,t-1}$), we observe that the estimated coefficients are significantly negative for periods II, III, and IV. From these significant negative estimates, we infer that a borrowing firm that depends on particular relationships more intensively is more likely to maintain its existing relationships.

For the equity increase ($\mathrm{EQUITY}_{i,t-1}$), its coefficients were estimated to be significantly negative for the period from 1996 to 2010. As for the two debt funding sources, the results show a significantly negative estimate for corporate bonds ($\mathrm{CB}_{i,t-1}$) and a significantly positive estimate for commercial paper ($\mathrm{CP}_{i,t-1}$) but only in period II. From the negative estimates for the equity increase and corporate bonds, we can infer that a firm that had more limited access to such external funding sources was more likely to maintain its existing relationships, particularly during the late 1990s. In contrast, the positive estimate for commercial paper indicates that a borrowing firm that had more limited access to the commercial paper market is more likely to terminate its relationships with lending banks. Given that only financially healthy firms can issue commercial paper, this could serve as a suitable proxy for the issuing firm's credit condition. If this were the case, for a firm that could not easily issue commercial paper, its bank–borrower relationships would be more likely to be terminated because of its relatively poor credit condition.

1.2.3 Estimation Results for Investment

Tables 1.4 and 1.5 report estimation results using two instrumental variables ($\text{WLEV}_{i,t}$and $\text{WEXP}_{i,t}^{Estate}$) on the pooled sample and the dynamic panel model, respectively. Table 1.5 reports estimation results obtained using the year dummy variables (Year) and the interaction terms between the industry and year dummy variables (Year $\times$ Ind) in columns (i) and (ii), respectively.[21] The interaction terms, Year $\times$ Ind, are aimed at controlling for unobserved time-varying industry effects on firm investment.

The two tables show that the termination variable ($\text{CUT}_{i,t}$) has significantly positive estimates only for period III (2001 to 2005), implying that the decrease in firm investment was significantly affected by bank-driven relationship terminations. Regarding the magnitude of the effect on firm investment, the point estimate is approximately 0.3 in the dynamic panel model, as shown in Table 1.5. This means that a 10% decline in bank loans as a result of lender-driven terminations led to a decrease in firm investment on average by 3%.

This estimated impact on firm investment is substantially larger than that in previous studies of credit supply shocks such as Amiti and Weinstein (2013).[22] The reason that our estimated impact is larger than the previous studies is that our

[21] The p-values of the Arellano–Bond test for autocorrelation in the first-differenced errors are reported in the bottom rows of Table 1.5. The results support the estimation assumption that there is no serial correlation in the original error, $\epsilon_{i,t}$.

[22] Amiti and Weinstein's (2013) estimation results (in their Table **??**) imply that a 10% decline in bank loans as a result of their bank supply shocks induced a decrease in firm investment by 1.2% in the 1990s and by 0.5% in the 2000s for firms with a loan-to-asset ratio of 0.196, which is its sample mean (see Appendix B in Amiti and Weinstein (2013)).

Table 1.4: Estimation Results for Firm Investment Equation: The Pooled Instrumental Variable Estimation Method

Period	(I)	(II)	(III)	(IV)
	1991–1995	1996–2000	2001–2005	2006–2010
Dependent variable: INVEST				
Independent variables:				
CUT	-0.960	-0.205	0.626*	0.186
	(0.973)	(0.401)	(0.365)	(1.331)
INVEST_{t-1}	-0.0003	0.108***	0.065***	-0.023
	(0.0742)	(0.027)	(0.021)	(0.029)
LEV	0.013	-0.023	-0.074***	-0.047
	(0.022)	(0.018)	(0.028)	(0.050)
LIQUID	0.040	0.035**	0.075***	0.017
	(0.026)	(0.017)	(0.023)	(0.034)
Q	0.005	0.010	0.013	0.022**
	(0.006)	(0.006)	(0.010)	(0.009)
ROA	0.429***	0.256***	0.191***	0.432***
	(0.139)	(0.062)	(0.067)	(0.146)
SALE	3.070*	2.790*	3.500***	3.339
	(1.578)	(1.493)	(1.336)	(2.341)
SIZE	0.166	-0.499***	-0.041	0.016
	(0.162)	(0.156)	(0.218)	(0.393)
AGE	-0.723	-1.312**	-4.448***	-5.495***
	(1.186)	(0.519)	(0.874)	(1.587)

Table 1.4: Estimation Results for Firm Investment Equation: The Pooled Instrumental Variable Estimation Method (continued)

Period	(I)	(II)	(III)	(IV)
	1991–1995	1996–2000	2001–2005	2006–2010
Dependent variable: INVEST				
Independent variables:				
NUMBER	-0.165	0.068	-0.291	0.373
	(0.368)	(0.311)	(0.522)	(1.889)
EQUITY	1.808***	1.649***	1.821**	2.409
	(0.463)	(0.464)	(0.857)	(2.464)
CB	0.017	0.022	0.125*	-0.032
	(0.025)	(0.021)	(0.068)	(0.069)
CP	-0.067	0.200**	0.055	-0.053
	(0.126)	(0.0856)	(0.143)	(0.279)
Year Dummy	✓	✓	✓	✓
Industry Dummy	✓	✓	✓	✓
N	7510	10322	10365	9551
Hansen J test	0.915	0.904	0.444	0.766
Anderson Rubin test	0.212	0.602	0.080	0.895

Notes: We conducted a pooled-instrumental-variable estimation to estimate firm outcome equation (1) and included firm investment in a firm outcome variable $y_{i,t}$. Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% levels of significance, respectively. The p-value of the Anderson-Rubin test is calculated by a bootstrap method, following Davidson and MacKinnon (2014). Hansen J test indicates the p-value.

Table 1.5: Dynamic Panel Estimation Results for the Firm Investment Equation with Fixed Effects

Period	(I)		(II)		(III)		(IV)	
Period	1991–1995		1996–2000		2001–2005		2006–2010	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Dependent variable: INVEST								
Independent variables:								
CUT	0.268	0.180	-0.169	-0.186*	0.231**	0.302**	0.229	0.157
	(0.186)	(0.177)	(0.107)	(0.113)	(0.118)	(0.119)	(0.234)	(0.186)
INVEST_{t-1}	-0.009	-0.006	0.029	0.037*	-0.020	-0.017	0.029	0.030
	(0.057)	(0.053)	(0.020)	(0.019)	(0.020)	(0.020)	(0.028)	(0.031)
LEV	-0.350**	-0.293**	-0.211*	-0.166	-0.058	-0.062	-0.021	-0.075
	(0.162)	(0.134)	(0.118)	(0.120)	(0.156)	(0.157)	(0.235)	(0.237)
LIQUID	1.167***	1.094***	0.904***	0.801***	0.345**	0.298*	0.242	0.180
	(0.151)	(0.145)	(0.194)	(0.191)	(0.155)	(0.171)	(0.264)	(0.278)
Q	-0.005	-0.008	-0.013	-0.011	-0.011	-0.011	0.0009	-0.003
	(0.005)	(0.006)	(0.013)	(0.014)	(0.021)	(0.020)	(0.0074)	(0.007)
ROA	0.104	0.045	-0.067	-0.092	-0.021	-0.024	0.086	0.037
	(0.198)	(0.116)	(0.065)	(0.067)	(0.061)	(0.057)	(0.130)	(0.106)
SALE	0.436	-0.041	1.058	1.004	0.777	0.467	1.266	1.155
	(0.948)	(0.846)	(0.857)	(0.845)	(1.189)	(1.202)	(2.270)	(2.268)
SIZE	-28.50***	-37.33***	-19.45***	-18.89***	-9.006**	-12.88**	-20.73***	-30.35***
	(5.066)	(6.004)	(5.293)	(5.553)	(4.457)	(5.216)	(8.015)	(8.667)
AGE	5.397	6.211	-12.68	-8.052	-19.42*	-13.25	-8.322	-12.37
	(17.34)	(17.31)	(10.78)	(11.77)	(11.62)	(13.47)	(10.86)	(14.25)

Table 1.5: Dynamic Panel Estimation Results for the Firm Investment Equation with Fixed Effects (continued)

Period	(I)		(II)		(III)		(IV)	
Period	1991–1995		1996–2000		2001–2005		2006–2010	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Dependent variable: INVEST								
Independent variables:								
NUMBER	-2.572	-3.389	1.167	0.136	1.691	0.914	-3.506*	-3.509
	(3.386)	(3.366)	(1.620)	(1.714)	(1.895)	(1.966)	(1.988)	(2.155)
EQUITY	0.401	0.348	0.327	0.379	0.757	0.549	-0.159	0.250
	(0.424)	(0.466)	(0.340)	(0.351)	(0.790)	(0.799)	(0.879)	(0.987)
CB	-0.022	-0.029**	-0.0002	0.0005	0.032	0.044	0.132**	0.102
	(0.014)	(0.014)	(0.0133)	(0.0134)	(0.028)	(0.027)	(0.066)	(0.066)
CP	-0.030	-0.0007	0.099*	0.109*	0.214*	0.240**	0.110	0.045
	(0.132)	(0.1440)	(0.056)	(0.059)	(0.120)	(0.118)	(0.103)	(0.112)
Dummy	Year	Year× Ind.	Year	Year× Ind.	Year	Year× Ind.	Year	Year× Ind.
N	7258	7258	8970	8970	9330	9330	8699	8699
Numb. of IVs	202	337	202	337	202	337	202	337
Hansen test (p-value)	0.009	0.104	0.551	0.545	0.024	0.337	0.087	0.169
Arellano-Bond test for AR(1)	0.018	0.020	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond test for AR(2)	0.407	0.388	0.926	0.989	0.389	0.491	0.426	0.419

Notes: We conducted the instrumental variable estimation of Arellano and Bond (1991), based on a dynamic panel specification with firm fixed effects to estimate firm outcome equation (1) including firm investments in a firm outcome variable $y_{i,t}$. We used the lagged values of the firm covariates ($\mathrm{FIRM}_{i,t-k}$, $k = 2, ..., 4$), the outcome variable ($y_{i,t-k}$, $k = 2, ..., 4$), the termination variable ($\mathrm{CUT}_{i,t-k}$, $k = 2, ..., 4$), the bank leverage ratio ($\mathrm{WLEV}_{i,t-1}$), and exposure to the real estate industry in 1989 ($\mathrm{WEXP}^{\mathrm{Estate}}_{i,t-1}$) as instrumental variables. Year and Year × Ind. indicate time dummy variables and the cross terms of the time dummy and industrial dummy variables, respectively. Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% levels of significance, respectively.

bank supply shocks involve credit decreases induced by relationship terminations, whereas their bank supply shocks involve credit decreases not only induced by relationship terminations, but also within existing relationships.

Given the macroeconomic conditions of the early 2000s, as reported in Table 1.2, this estimate also implies a substantial effect on the real economy. The sample average firm investment was only 0.42% during this period, but the average impact of bank-driven terminations on firm investment is approximately −1.03%.[23]

As for period II (1996 to 2000), Tables 1.4 and 1.5 show that all estimated coefficients for the termination variable are not significant, except in the dynamic panel estimation with the industry-year dummies. We should note that the dynamic panel estimation for this period does not suffer from the weak instrument problem, as demonstrated in the previous subsection. These estimation results for period II imply that bank-driven terminations did not decrease firm investment in the late 1990s, even though some existing studies, including Woo (2003) and Watanabe (2007), have purportedly found evidence of a credit crunch during this period. In Section 1.3, we consider why bank-driven terminations led to a decrease in firm investment in the early 2000s but not in the late 1990s.

For periods I and IV, Tables 1.4 and 1.5 suggest that the termination variable does not yield significant estimates. Given that bank exposure to the real estate industry ($\mathrm{WEXP}_{i,t}^{Estate}$) and the bank book leverage ratio ($\mathrm{WLEV}_{i,t}$) are weak instruments for the termination variable in these periods, as demonstrated in the previous subsection, we cannot correctly infer the effect of relationship terminations during these periods.

Table 1.4 also reports the p-value of the Anderson-Rubin test statistic for the pooled-data estimation to show the robustness of the significance of the termination variable ($\mathrm{CUT}_{i,t}$). The Anderson-Rubin test allows us to test the significance of the termination variable (b_{cut}) in equation (1), ensuring robustness with respect to the weak instrument problem. In this paper, following a restricted efficient bootstrap method proposed by Davidson and MacKinnon (2014), we calculated the

[23] The average impact is calculated by $b_{cut} \times \mathrm{CUT}_{i,t}$ in firm outcome equation (1). As reported in Table 1.2, the sample averages of the termination variable ($\mathrm{CUT}_{i,t}$) and firm investment ($\mathrm{INVEST}_{i,t}$) from 2001 to 2005 are −3.43% and 0.42%, respectively.

bootstrap p-value of the Anderson-Rubin test statistic with 5,000 replications.[24] The Anderson-Rubin test statistics show that for period III, the effects of relationship terminations are significant at the 10% level, even after considering the weak instrument problem, while for periods I, II and IV, they are not significant at any conventional level.

We should note that compared with the results from the pooled sample estimation, the results from the panel fixed effects model demonstrate the more moderate effect of the termination variable in period III. This could be because the pooled data (nonpanel setting) estimation does not control for unobserved factors in the firm investment equation, and thus the estimates would have been biased, as discussed in Subsection 1.3.4. Considering such estimation bias can arise from the unobserved firms' factors, we below focus on the estimation results based on the dynamic panel model with firm fixed effects.

As for the firm covariates ($\mathbf{FIRM_{i,t-1}}$) in periods II and III, the estimates are significant only for the liquidity ratio ($\mathrm{LIQUID}_{i,t-1}$), firm size ($\mathrm{SIZE}_{i,t-1}$), and commercial paper ($\mathrm{CP}_{i,t-1}$) in both year dummy specifications. For the liquidity ratio, its estimated coefficients are positive, indicating that firms with a higher liquid asset ratio were more likely to increase their investment. The negative estimates for firm size imply that smaller firms tended to invest more. The commercial paper variable displays positive estimates, indicating that firms that increased their dependence on corporate bonds were more likely to increase investment.[25]

[24]Note that we do not use the bootstrap method to deal with the problem of a small sample size. Davidson and MacKinnon (2014) proposed that one should not use confidence sets obtained by simply inverting the Anderson-Rubin test because these would not have correct coverage, irrespective of the sample size. They demonstrated that the confidence sets obtained by the restricted efficient bootstrap method provided better coverage than that obtained by simply inverting the Anderson-Rubin test. See Davidson and MacKinnon (2014) for a restricted efficient bootstrap procedure.

[25]Gan (2007b) showed that collateral loss would lead to a decrease in firm investment. We also included the collateral-to-loan ratio (defined as tangible assets over outstanding borrowings) as well as the interest coverage ratio (defined by dividing EBIT, or the earnings before interest and taxes, by total interest payments) into the investment function. Their estimated coefficients are positive, albeit insignificant, indicating that firms facing decreases in the collateral-to-loan and interest coverage ratios were more likely to decrease investment.

1.2.4 Validity and Exclusion Restriction of Instruments

In our estimations thus far, we have used the weighted average of the bank book leverage ratio ($\mathrm{WLEV}_{i,t}$) and bank exposure to the real estate industry ($\mathrm{WEXP}_{i,t}^{Estate}$) as instrumental variables.

As we control both observed and unobserved firm factors using various firm covariates and firm fixed effects in the panel regression, the two instruments are expected to be orthogonal to the error terms. To investigate whether our instrumental variables satisfy the validity condition in estimating the dynamic panel model with fixed effects, we conduct the C test, which is a variant of the Hansen test of the overidentification restrictions on the bank instrumental variables.[26]

Table 1.6 reports the C test statistics for the orthogonality of our two instrumental variables in the dynamic panel model with firm fixed effects. The C test statistics for the two instruments show that the null hypothesis of their orthogonality is not rejected at at the 5% significance level for all subsample periods. This indicates that our estimation results thus far are not contaminated by the endogeneity problem of the two bank instrumental variables.[27]

Another concern about the validity of our instrumental variables is whether they satisfy the exclusion restriction. To investigate this issue, we test the significance of the instrumental variables by including them in the firm investment equation. Thus, we find that the instrumental variables are not significant at the 10% significance level, which implies that the exclusion restriction is not violated.

[26]The C test statistic is the difference between two J statistics: one based on the full set of overidentification restrictions and the other based on the subset of the restrictions in which only the tested instrumental variables are removed. Under the condition that the subset of the restrictions is satisfied, we test the null hypothesis that the removed instruments are orthogonal to the error terms. The C test statistic has a χ^2 distribution with degrees of freedom equal to the number of instruments being tested under the null hypothesis.

[27]Tables 1.4 and 1.5 report the p-values for a Hansen test of the orthogonality condition in the pooled sample and dynamic panel specifications, respectively. The p-values indicate that the orthogonality condition is not rejected for almost all cases (the exceptions are the dynamic panel specifications including the time dummy variables (Year) reported in 1.5).

Table 1.6: Validity of Instruments

Period	(I) 1991–1995	(II) 1996–2000	(III) 2001–2005	(IV) 2006–2010
C test (p-value) with year dummies	0.988	0.081	0.567	0.643
C test (p-value) with year-industry dummies	0.537	0.239	0.918	0.210

Notes: The null hypothesis is that the two instruments, the bank leverage ratio ($\mathrm{WLEV}_{i,t}$) and exposure to the real estate industry in 1989 ($\mathrm{WEXP}_{i,t}^{\mathrm{Estate}}$), are orthogonal to the error term in firm outcome equation (1) including firm investment in the firm outcome variable $y_{i,t}$. The C test statistic has a χ^2 distribution with two degrees of freedom. The C test statistic is calculated on the basis of the estimation results shown in Table 1.5.

1.3 Background Mechanism for the Termination Effects

In the previous section, we found the following evidence. First, in the first-stage regression, the bank leverage ratio was a significant determinant of relationship terminations in the 1990s, while the bank exposure to the real estate industry in 1989 was significant in the period of the early 2000s. As for the late 2000s, both instrumental variables were not significant determinants. Additionally, only in periods II and III did we reject the weak instrument hypothesis. Second, the lender-driven relationship terminations had significant negative effects on firm investment but only in the early 2000s. In this section, we explore the reasons for the differences in estimation results across the subsample periods.

1.3.1 Financial Background

In this subsection, we discuss the financial background that likely invoked the differences in estimation results. One promising explanation of the difference in the estimation results across each subsample period is that Japanese banks faced low capital levels relative to the regulatory minimum in the 1990s, whereas from the early 2000s onwards, they struggled to write off nonperforming loans after meeting their capital standards. This difference would make the effects of terminations more significant in the early 2000s because they destroyed relation specific assets in more tight relationships and the matching process was severely inefficient in the early 2000s.

In 1988, bank regulators in major industrial countries agreed to standardize capital requirements internationally, through the so-called Basel Accord. Subsequent to this, all Japanese banks struggled to meet these capital standards for much of the 1990s. During this period in Japan, land and stock prices fell continuously. Consequently, many loans granted during the bubble period of the late 1980s became nonperforming, and bank capital gains, which are a component of Tier II capital, decreased. Accordingly, banks that were more impaired and had less capital issued additional subordinated debt to inflate their bank capital. They were able to do so because, within the local Japanese rule governing capital requirements, subordinated debt can be counted as Tier II capital, as pointed out by Ito and Sasaki (2002) and Montgomery (2005).[28]

In the 1990s, this regulatory forbearance policy had caused Japanese banks to engage in a "patching up" of their capital ratios (see, e.g., Shrieves and Dahl (2003) and Peek and Rosengren (2005)). In the late 1990s, the attitude of the Japanese government and regulatory authorities toward Japanese banks started to change by allowing them to enter bankruptcy and by conducting capital injections. In evidence, in 1998 and 1999, the government of Japan decided to infuse a large amount of capital into poorly capitalized banks in order to increase their capital adequacy ratios. These large-scale public capital injections allowed almost all Japanese banks to meet their capital standards (see, e.g., Watanabe (2007), Allen et al. (2011), and Nakashima (2016) for the Japanese bank recapitalization programs). However, the amount of nonperforming loans in Japanese banks only started to decrease after the Financial Revitalization Program (hereafter, FRP), or the so-called Takenaka Plan, was executed in 2002 (see Sakuragawa and Watanabe (2009) for details).

[28] As shown by Skinner (2008), Japanese banks have also used deferred tax assets to compensate for capital losses arising from unrealized losses on their holding stocks. This is because the government allowed banks to account for their deferred tax assets as Tier I capital in 1998. Bank managers at their discretion estimated subjectively the total amount of deferred tax assets.

Before the execution of the FRP, the amount of nonperforming loans increased continuously from the early 1990s to the late 1990s. In 2002, the maximum was about 53 trillion yen. Generally speaking, in the 1990s, Japanese banks suffered from low capital levels and thus struggled to increase their capital ratios, while they did not completely solve the problem of nonperforming loans. Such a financial background in the 1990s is probably one of the reasons that the bank leverage ratio was a determinant of the relationship terminations that took place during the 1990s but not the early 2000s, as demonstrated in Subsection 1.2.2.

It also explains why these terminations had significant effects in the early 2000s but not in the late 1990s, as demonstrated in Subsection 1.2.3. Japanese banks were able to support some firms that were in need of funds by accumulating nonperforming loans in the late 1990s (see Peek and Rosengren (2005) and Caballero et al. (2008)). Indeed, during this period, the decrease in the aggregate amount of bank loans caused by terminations was relatively small compared with those in the early 2000s (see the sample average of the termination variable in Figure 1.5), though the number of terminations was much larger (see the number of terminations in Figure 1.2). This also meant that it was more likely that less important bank–firm relationships were terminated in the late 1990s, while in the early 2000s, important relationships were also terminated. [29]

The FRP did not allow the banks to meet their capital requirement by engaging in regulatory capital arbitrage. It instead requested that the banks apply a stricter standard than before when disclosing the amount of nonperforming loans on their books. After the execution of the FRP in 2002, banks with impaired capital actively pursued the write-off of their nonperforming loans. Consequently, by 2005, the amount of nonperforming loans drastically decreased to about 20 trillion yen. This difference in bank financial background during the 1990s and the early 2000s should be responsible for the estimation results that point to the effect of bank-driven terminations on firm investment during the early 2000s, but not the late 1990s.

Japanese banks had improved their capital quality and quantity before the

[29]The average loss of firm's borrowing exposure due to one termination was about 6% in the late 1990s, but increased to about 12% in the early 2000s.

late 2000s. Thus, during the late 2000s, they remained financially sound and retained their financial intermediation function in response to firm funds demand amid the turmoil of the 2008 financial crisis (see Uchino (2013)). Such soundness of Japan's banking system is responsible for the estimation results indicating that our two instrumental variables—as proxies for the impairment of bank balance sheets—were not associated with the termination of bank–borrower relationships.

1.3.2 New Relationships

In this subsection, we present evidence that the condition of the bank loan market was actually different between the late 1990s and the early 2000s, by answering the following question: were firms immediately able to establish new relationships in response to these terminations? The bank-driven termination effects should be mitigated if the borrowing firms that faced these bank-driven terminations were immediately able to switch to other borrowing relationships. To investigate this question, we introduce the following discrete choice probit model of the establishment of a firm's new relationships in response to existing relationship terminations:

$$MARRY_{i,t} = \begin{cases} 1 & \text{if } z_{i,t} \geq 0, \\ 0 & \text{if } z_{i,t} < 0, \end{cases}$$

$$z_{i,t} = \alpha + \beta \text{MARRY}_{i,t-1} + \gamma_1 \text{CUT}_{i,t} + \gamma_2 \text{CUT}_{i,t-1} + \mathbf{\Gamma' FIRM_{i,t-1}} + \mathbf{\Lambda' D_t} + \mathbf{u_{i,t}}, \quad (1.8)$$

where $\text{MARRY}_{i,t}$ denotes an indicator variable that takes a value of one if firm i establishes a new relationship in fiscal year t. $\text{CUT}_{i,t}$ denotes termination variable (2): the decreasing rate of firm i's outstanding bank borrowings caused by relationship terminations in fiscal year t. $\mathbf{FIRM_{i,t-1}}$ and $\mathbf{D_t}$ indicate a vector of borrower-side covariates and year dummy variables, respectively.

We specify the model for relationship terminations and establishments as shown in equations (7) and (8), respectively.[30] To estimate the relationship switch-

[30]For the switching system, we assume that the stochastic error terms (e_{it}, u_{it}) in equations (7) and (8) follow an identically distributed multivariate normal distribution $N(\mathbf{0},\ \mathbf{\Sigma})$ for all

ing system, we employ the bank leverage ratio ($\mathrm{WLEV}_{i,t}$) and bank exposure to the real estate industry in 1989 ($\mathrm{WEXP}_{i,t}^{Estate}$) as instruments for the termination variable.

Table 1.7 reports the estimation results for relationship establishment equation (8). This table clearly shows that the termination variable ($\mathrm{CUT}_{i,t}$) yields significantly negative estimates for period II but not for period III. These results imply that in the early 2000s, firms that faced bank-driven terminations did not establish new relationships, while in the late 1990s, they were likely to do so immediately.

These estimation results for the switching system provide a clearer picture of the working mechanism linking bank–borrower relationships and firm investment during the period from the late 1990s to the early 2000s. The results reported in the previous section show that lender-driven relationship terminations affected firm investment in the early 2000s but not in the late 1990s. The results for the switching system in this section imply that in the late 1990s, finding new relationships was likely to mitigate the negative shocks of bank-driven terminations on investment. On the other hand, in the early 2000s, firm investments were exposed to the negative shocks of bank-driven terminations, because they did not establish new relationships.

Regarding period IV, the termination variable has a significantly positive estimate. This implies that firms facing terminations experienced difficulties in finding new relationships. However, as discussed in Subsection 1.2.2, we are unable to infer correctly the effects of the terminations in period IV because of the weak instrument problem.

The estimates of the coefficient on the one-period lag of the termination variable ($\mathrm{CUT}_{i,t-1}$) are significantly negative for subsample periods II, III, and IV. This result indicates that firms were able to establish new relationships at least one year subsequent to experiencing relationship termination. In Subsection 1.4.3, we reconsider the implications of the estimation results for the two termination variables, $\mathrm{CUT}_{i,t}$ and $\mathrm{CUT}_{i,t-1}$, when we analyze for how long the bank-driven

firms i, where $\mathbf{\Sigma}$ is not block diagonal between e_{it} and u_{it}.

Table 1.7: Estimation Results for the New–Relationship Equation

Period	(I) 1991–1995	(II) 1996–2000	(III) 2001–2005	(IV) 2006–2010
Dependent variable: MARRY				
Independent variables:				
CUT	-0.117	-0.063*	-0.006	0.099***
	(0.072)	(0.038)	(0.021)	(0.017)
Lag CUT	-0.010	-0.016*	-0.014***	-0.019***
	(0.012)	(0.0090)	(0.003)	(0.007)
MARRY	0.369*	0.293***	0.357***	0.306***
	(0.218)	(0.0901)	(0.040)	(0.110)
Lag INVEST	0.0001	0.004***	-0.0005	-0.0006
	(0.0012)	(0.001)	(0.0006)	(0.0007)
LEV	0.009***	0.007***	0.008***	-0.001
	(0.002)	(0.001)	(0.001)	(0.003)
LIQUID	-0.003*	-0.003**	-0.005***	-0.00005
	(0.002)	(0.001)	(0.001)	(0.00175)
Q	-0.0011**	-0.0007**	-0.0003	0.0004*
	(0.0005)	(0.0003)	(0.0003)	(0.0002)
ROA	0.007	0.013***	0.004	-0.006
	(0.005)	(0.004)	(0.003)	(0.005)
SALE	0.233**	0.309***	0.175**	-0.051
	(0.116)	(0.099)	(0.077)	(0.059)
SIZE	0.055**	0.035**	0.033**	0.026*
	(0.028)	(0.017)	(0.013)	(0.015)
AGE	0.014	-0.249***	-0.190***	-0.132*
	(0.107)	(0.055)	(0.042)	(0.070)

Table 1.7: Estimation Results for the New–Relationship Equation (continued)

Period	(I) 1991–1995	(II) 1996–2000	(III) 2001–2005	(IV) 2006–2010
Dependent variable: MARRY				
Independent variables:				
NUMBER	-0.056	-0.007	-0.005	0.131***
	(0.046)	(0.040)	(0.032)	(0.037)
EQUITY	0.051	-0.002	0.085**	0.165***
	(0.041)	(0.037)	(0.041)	(0.045)
CB	-0.009***	-0.010***	-0.006**	-0.0005
	(0.003)	(0.002)	(0.003)	(0.0038)
CP	0.012	0.001	-0.004	-0.007
	(0.017)	(0.013)	(0.013)	(0.013)
Dummy	Year	Year	Year	Year
N	7507	10320	10345	9533

Notes: We conducted the pooled-instrumental-variable estimation to estimate relationship-switching model (8). Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% levels of significance, respectively.

termination shocks lasted.[31]

For the one-period lag of the new relationship indicator (MARRY$_{i,t-1}$), we estimate the coefficients to be significantly positive. These positive estimates imply that firms that were able to establish new relationships in year $t-1$ were more likely to establish new relationships in year t; that is, the relationship establishment of borrowing firms exhibits some persistence.

Estimation results for the firm covariates in switching equation (8) can be summarized as follows: a firm that has a relatively strong funding need–that is, large and highly leveraged with a low liquid assets ratio, but young with a high growth rate of sales–is more likely to establish new bank–borrower relationships.

1.3.3 Continuing Relationships

In the previous subsection, we found that firms that faced bank-driven terminations in the late 1990s immediately established new relationships, whereas, in the early 2000s, it took those firms at least one year to find and establish new relationships. The other possible alternative strategy for firms experiencing terminations is to increase their borrowing from their existing relationships.

In this subsection, we investigate the following question: were firms that faced bank-driven terminations immediately able to increase bank borrowings within their existing relationships? To address this question empirically, we include the log-difference of the outstanding amount of bank loans defined in continuing relationships (CONTINUE$_{i,t}$) in the outcome variable $y_{i,t}$ in equation (1). To estimate equation (1), we conduct instrumental variable estimation based on the dynamic panel specification with firm fixed effects, using the same instruments (WLEV$_{i,t}$ and WEXP$_{i,t}^{Estate}$) as in the previous analyses.

Table 1.8 reports the estimation results for each subsample period. Focusing on the difference between the financially distressed periods II and III, the

[31]We also estimated equations (7) and (8), by replacing the new relationship variable in year t (MARRY$_{i,t}$) with that in year $t+1$ (MARRY$_{i,t+1}$) as a dependent variable in equation (8). Then we obtained the evidence that the coefficients on the termination variable in year t (CUT$_{i,t}$) are significantly negative for periods II and III. This implies that a firm that faced bank-driven termination was able to establish a new relationship one year after the termination.

termination variable ($\mathrm{CUT}_{i,t}$) has a significantly negative estimate in period II but not in period III. From these estimation results, we infer that in the late 1990s, firms that faced bank-driven terminations were able to increase bank borrowings promptly within their existing relationships, while in the early 2000s, similar firms were unable to do the same.

Summing up the estimation results for the firm covariates, we note that a highly leveraged firm with diversified debt financing, that has many relationships and easy access to corporate bond markets, was more likely to decrease its bank borrowings within its continuing relationships.

1.3.4 Asymmetric Information Problem and the Termination Effect

In the above, we showed that the termination effect was significant in the early 2000s, when firms facing termination were generally unable to find alternative funding sources. However, theoretical models (Den Haan et al. (2003), Wasmer and Weil (2004), and Becsi et al. (2005; 2013)) predicted that the effect of terminations should vary depending on the extent of asymmetric information problems. To investigate this point, we estimate the termination effect by dividing our sample into different subsamples based on two proxies for the degree of asymmetric information problem that a firm faces. The first proxy is firm size, defined as the total book value of assets, and the second proxy is the issue of corporate bonds.

The reason that we use corporate bond issues to proxy the degree of the asymmetric information problem is that in Japan, not all firms are easily able to issue corporate bonds because there is no liquid junk bond market. Accordingly, Japanese firms need to have established a good reputation in financial markets before they can issue bonds. Therefore, the issue of corporate bonds serves as a proxy for the degree of establishment of a firm's reputation in funding markets; in other words, we can consider Japanese firms issuing corporate bonds to be those relatively less affected by asymmetric information problems.

Table 1.9 reports the estimated coefficients obtained by dividing our sample

Table 1.8: Estimation Results for the Firm Borrowing in a Continuing Relationship

Period	(I) 1991–1995	(II) 1996–2000	(III) 2001–2005	(IV) 2006–2010
Dependent variable: CONTINUE				
Independent variables:				
CUT	-0.514	-0.953***	0.0537	-0.447
	(0.778)	(0.342)	(0.296)	(0.338)
Lag CONTINUE	-0.0598**	-0.0548***	-0.0715***	-0.106***
	(0.0240)	(0.0202)	(0.0191)	(0.0185)
LEV	-0.829*	-1.149**	-0.415***	-1.728***
	(0.457)	(0.536)	(0.115)	(0.436)
LIQUID	0.384	-0.195	-0.0263	0.512
	(0.389)	(0.437)	(0.334)	(0.340)
Q	-0.0386	0.0528	0.0855*	0.124***
	(0.0252)	(0.0448)	(0.0454)	(0.0457)
ROA	-0.454	-0.313*	-0.343***	-0.230
	(0.328)	(0.179)	(0.106)	(0.153)
SALE	0.660	3.823	-3.434	-0.356
	(2.315)	(3.229)	(2.432)	(2.167)
SIZE	-50.46***	3.628	-22.47*	-14.95
	(18.03)	(18.97)	(12.41)	(16.67)
AGE	40.96	-60.04	-21.21	-3.996
	(56.47)	(39.56)	(27.91)	(16.83)

Table 1.8: Estimation Results for the Firm Borrowing in a Continuing Relationship (continued)

Period	(I) 1991–1995	(II) 1996–2000	(III) 2001–2005	(IV) 2006–2010
Dependent variable: CONTINUE				
Independent variables:				
NUMBER	-22.80**	-27.48***	-18.50***	-18.29***
	(9.561)	(7.423)	(5.725)	(5.929)
EQUITY	-1.742	0.585	-2.821	-3.571
	(1.644)	(1.372)	(2.036)	(2.237)
CB	-0.490***	-0.646***	-0.602***	-0.633***
	(0.0807)	(0.0928)	(0.102)	(0.112)
CP	-0.0757	-0.0844	0.578	0.610
	(0.353)	(0.293)	(0.402)	(0.503)
Dummy	Year × Ind.	Year × Ind.	Year × Ind.	Year × Ind.
N	7293	9296	9668	9023
Hansen Test (p-value)	0.032	0.111	0.149	0.015
Arellano–Bond test for AR(1), p-value	0.000	0.000	0.000	0.000
Arellano–Bond test for AR(2), p-value	0.661	0.592	0.820	0.231
Num. of IVs	292	292	292	292

Notes: We conducted the instrumental variable estimation with dynamic panel model of Arellano and Bond (1991) to estimate firm outcome equation (1), and included firm borrowings within its continuing relationships in a firm outcome variable $y_{i,t}$. We used the lagged values of the firm covariates ($\text{FIRM}_{i,t-k}$, $k = 2, 3$), the independent variable ($y_{i,t-k}$, $k = 2, 3$) and the termination variable ($\text{CUT}_{i,t-k}$, $k = 2, 3$), and two bank variables ($\text{WLEV}_{i,t-1}$ and $\text{WEXP}^{\text{Estate}}_{i,t-1}$) as instrumental variables. Year × Ind. indicate time dummy variables and the cross terms of the time dummy and industrial dummy variables, respectively. Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% levels of significance, respectively.

for 2001–05 based on firm size or the issue of corporate bonds.[32] For firm size, we split the sample into three different subsamples based on the total book value of assets as of the beginning of fiscal year 2001, and report the estimation results for each subsample in the first to third columns. The estimated effects of termination are significant for small- and medium-sized firms but not for large firms. This coincides with the prediction of the theoretical models: large firms suffer less from asymmetric information problems and hence are relatively easily able to find an alternative funding source. This suggests the mitigation of the effect of bank-driven terminations for large firms.

The estimation results for the subsamples of firms with and without corporate bonds are in the fourth and fifth columns in Table 1.9, respectively. The estimate for the termination variable is not significant for firms issuing corporate bonds but is significant for firms without them. These results imply the mitigating effects of bank-driven terminations for firms that have established some reputation in credit markets by issuing corporate bonds. Our empirical analysis conducted in this subsection reveals the importance of the asymmetric information problem in examining the effect of bank-driven terminations.

1.3.5 A Background Mechanism for the Termination Effect

The above estimation results provide a clearer insight into the background mechanism for the bank-driven termination effect on firms facing relationship terminations. In the late 1990s, when less important relationships for borrowing firms were terminated and bank-driven relationship terminations had no significant effects on firm investment, firms facing relationship terminations were able to switch to new relationships immediately or to increase their borrowings within their existing relationships to meet their demand for loans. Meanwhile, in the early 2000s, when more important relationships for borrowing firms were terminated and bank-driven relationship terminations exerted significant effects on firm investment, these firms were unable to make up for the lack of funding result-

[32]We report the estimation results based on period III of the early 2000s only. For the other subsample periods I, II and IV, we did not identify any significant effect on firm investment, even if we split the subsamples based on the two asymmetric information proxies.

Table 1.9: Termination Effect with Different Firm Size and Corporate Bond Market Access in 2001–2005

	Firm Size			Corporate Bond	
	Small	Medium	Large	Without CB	With CB
Dependent variable: INVEST					
Independent variable:					
CUT	0.300*	0.424*	0.083	0.344**	0.092
	(0.178)	(0.225)	(0.120)	(0.144)	(0.098)
Dummy	Year	Year	Year	Year	Year
N	2779	3108	3215	5843	3487
Hansen test (p-value)	0.112	0.496	0.234	0.095	0.278
Arellano-Bond test for AR(1), p-value	0.009	0.016	0.030	0.000	0.067
Arellano-Bond test for AR(2), p-value	0.050	0.589	0.824	0.103	0.200

Notes: We conducted the instrumental variable estimation of Arellano and Bond (1991), based on a dynamic panel specification with firm fixed effects to estimate firm outcome equation (1) including firm investments in a firm outcome variable $y_{i,t}$. We used the lagged values of the firm covariates, the outcome variable, and the termination variable as instrumental variables. Parameter estimates are obtained by also using the bank leverage ratio ($\mathrm{WLEV}_{i,t-1}$) and bank exposure to the real estate industry in 1989 ($\mathrm{WEXP}^{\mathrm{Estate}}_{i,t-1}$) as instruments. Other independent variables are included in our estimation but not reported in the table. Corporate bonds includes both straight and convertible bonds. *, **, and *** indicate 10%, 5%, and 1% levels of significance, respectively. Robust standard errors are in parentheses.

ing from relationship termination. In addition, such real effects of bank-driven terminations were more pronounced for relatively small firms facing more severe asymmetric information problems.

1.4 Extensions and Robustness Check

This section extends our analysis of the bank-driven terminations of relationships by conducting a robustness check. In particular, we develop our empirical analysis for period III, or the sample period from 2001 to 2005, when the decrease in borrowings because of lender-side terminations led to a decrease in firm investment. All analyses of firm investment in this section employ the dynamic panel model with firm fixed effects.

1.4.1 Bank Loan Changes in Terminations and Existing Relationships

In Section 1.2, we found that bank-driven terminations negatively affected firm investment. However, these results do not necessarily imply that a termination has a more significant effect on firms' investment than a change in the borrowing within existing relationships.

To show more clearly that the termination variable contains more important information about financial frictions–that is, search frictions in credit markets and the loss of relation-specific assets–that firms are facing, we run the dynamic panel regression by adding one variable, $\mathrm{CONTINUE}_{i,t}^{LOAN}$, to the baseline model with firm fixed effects. This variable is defined as follows:

$$\mathrm{CONTINUE}_{i,t}^{LOAN} = 100 \times \frac{\sum_{j \in B_{i,t-1}} (\mathrm{X}_{i,j,t} - \mathrm{X}_{i,j,t-1}) {\delta^{C}}_{i,j,t}}{\sum_{j \in B_{i,t-1}} \mathrm{X}_{i,j,t-1}}, \tag{1.9}$$

where ${\delta^{C}}_{i,j,t}$ denotes an indicator variable that takes a value of one if a relationship continues.

In addition, we also include the interaction term, $\mathrm{CONTINUE}^{LOAN} *$ $\mathrm{DECREASE}_{i,t}$, of the variable $\mathrm{CONTINUE}_{i,t}^{LOAN}$ and the indicator variable for firms with decreasing bank loans, $\text{DECREASE}_{i,t}$: $\text{DECREASE}_{i,t} = 1$ if $\text{CONTINUE}_{i,t}^{LOAN} < 0$, and otherwise $\text{DECREASE}_{i,t} = 0$. Thus, focusing on the estimated coefficients on the two variables, $\text{CONTINUE}_{i,t}^{LOAN}$ and $\text{CONTINUE}^{LOAN} * \text{DECREASE}_{i,t}$, we directly compare the effect of losses in credit through bank-driven terminations with that of decreases in credit within continuing relationships. Table 1.10 reports the dynamic panel estimation results.[33]

The estimation results indicate that the termination variable ($\text{CUT}_{i,t}$) has a significant effect on a firm's investment, whereas changes in borrowings within continuing relationships ($\text{CONTINUE}_{i,t}^{LOAN}$) does not. Furthermore, we find that the coefficient on the termination variable ($\text{CUT}_{i,t}$) is significantly larger than the sum of those on $\text{CONTINUE}^{LOAN} * \text{DECREASE}_{i,t}$ and $\text{CONTINUE}_{i,t}^{LOAN}$ at the 5% significance level by conducting the Wald test. This indicates that bank-driven terminations would have larger effects on firm investment than decreases in bank borrowings within continuing relationships.

The larger impact of relationship terminations on firm investment coincides with our hypothetical prediction that a termination of relationships provokes a significant effect on firm investment, while a decrease in loans within existing relationships has a relatively small effect, because firms expect that they may be able to finance investment through existing relationships without suffering from search frictions and the loss of relation-specific assets.

1.4.2 Supply-side Effects and Firms with Increasing Bank Loans

Another concern is that the results for the negative effect of the termination variable, as shown in Section 1.2, may have been obtained because our termination variable, $\text{CUT}_{\text{i,t}}$, served as a variable that only picked up distressed firms whose

[33]To estimate the dynamic panel model with the additional two bank loan variables, we used the intensity and duration of bank-borrower relationships as their instruments. The intensity is defined as the average of the firm's borrowing exposure to a particular bank, and the duration is defined as the weighted average of the durations of the firm's relationships, where the weight is defined as each firm's borrowing exposure to a lending bank. For the intensity, we also used each firm's maximum borrowing exposure to its main bank, but the results did not qualitatively change.

Table 1.10: Estimation Results with Growth Rates of Bank Loans in Continuing Relationships and New Relationships

	(III) 2001–2005
Dependent variable: INVEST	
Independent variables:	
CUT	0..287***
	(0.100)
CONTINUE$^{\text{LOAN}}$	0.001
	(0.927)
CONTINUE$^{\text{LOAN}}$*DECREASE	0.094*
	(0.078)
N	9330
Dummy	Year × Industry
Num. of IVs	614
Hansen test (p-value)	0.855
Arellano-Bond test for AR(1), p-value	0.000
Arellano-Bond test for AR(2), p-value	0.411

Notes: We conducted the instrumental variable estimation of Arellano and Bond (1991), based on a dynamic panel specification with fixed effects to estimate firm outcome equation (1) including firm investment in the firm outcome variable $y_{i,t}$. We used the lagged values of the firm covariates ($\text{FIRM}_{i,t-k}$, $k = 2, ..., 7$), the outcome variable ($y_{i,t-k}$, $k = 2, ..., 6$), the termination variable ($\text{CUT}_{i,t-k}$, $k = 2, ..., 8$), the continue variable ($\text{CONTINUE}^{\text{LOAN}}_{t-k}$ and $\text{CONTINUE}^{\text{LOAN}}\text{*DECREASE}_{t-k}$, $k = 2, ..., 8$), the two bank variables ($\text{WLEV}_{i,t-1}$ and $\text{WEXP}^{\text{Estate}}_{i,t-1}$), the intensity and duration of relationships as instrumental variables. Other independent variables are included in our estimation but not reported in the table. Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5% and 1% levels of significance, respectively.

bank borrowings decreased. If this is the case, then the estimation results do not show evidence of supply-side effects.

We conduct another analysis to show that the estimated coefficients on the termination variable accurately capture supply-side effects. To this end, we only use a select sample of firms with increasing bank loans in year t. If bank-driven terminations still exert significant effects on a firm's investment for this selected sample, it implies that the negative effects of bank-driven terminations on firm investments are more likely to be due to bank supply shocks because this test is based on relatively viable firms with stronger fundamentals and thus increasing bank loans.

Table 1.11 shows the estimation results obtained using the selected sample. The estimated coefficient on the termination variable ($\mathrm{CUT}_{\mathrm{i,t}}$) is significantly positive even in the selected sample. This indicates that the termination variable is more than a simple label for distressed firms whose outstanding borrowing decreases; hence, our estimated effects of bank-driven terminations succeed in capturing bank supply shocks.

1.4.3 Persistence of the Termination Effect

In this subsection, we examine how long the bank-driven termination effects last. This experiment is then the flip side of that hypothesis developed in Subsections 1.3.2 and 1.3.3, in which we sought to determine whether firms that face bank-driven terminations could find alternative funding for their investments by establishing new relationships or increasing their borrowings within their existing relationships. If bank-driven termination effects on firm investment disappear within a year after termination, we could infer that these firms are able to finance their investments by establishing new relationships or increasing their borrowings within their existing relationships. To estimate the persistence of the bank-driven termination effect, we include not only the contemporaneous but also four-year lags of the termination variable as independent variables.

Table 1.12 reports the estimated coefficients on the contemporaneous and four-year lags of the termination variable. The estimated termination effect on

Table 1.11: Estimation Results for Firms with Increasing Bank Loans

	(III) 2001–2005
Dependent variable: INVEST	Firms with Increasing Loans
Independent variables:	
CUT	0.326**
	(0.146)
N	3930
Dummy	Year
Num. of IVs	307
Hansen test (p-value)	0.229
Arellano–Bond test for AR(1), p-value	0.003
Arellano–Bond test for AR(2), p-value	0.926

Notes: We conducted the instrumental variable estimation of Arellano and Bond (1991), based on a dynamic panel specification with fixed effects to estimate firm outcome equation (1) including firm investment in the firm outcome variable $y_{i,t}$ only for firms with increasing bank loans. We used the lagged values of the firm covariates ($\text{FIRM}_{i,t-k}$, $k = 2, ..., 4$), the outcome variable ($y_{i,t-k}$, $k = 2, ..., 4$), the termination variable ($\text{CUT}_{i,t-k}$, $k = 2, ..., 6$), and two bank variables ($\text{WLEV}_{i,t-1}$ and $\text{WEXP}^{\text{Estate}}_{i,t-1}$) as instrumental variables. Other independent variables are included in our estimation but not reported in the table. Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5% and 1% levels of significance, respectively.

Table 1.12: Persistence of the Bank-driven Relationship Terminations in 2001–2005

Dependent variable: INVEST					
Independent variable:	$\mathrm{CUT_{it}}$	$\mathrm{CUT_{it-1}}$	$\mathrm{CUT_{it-2}}$	$\mathrm{CUT_{it-3}}$	$\mathrm{CUT_{it-4}}$
	0.219**	0.006	-0.008	-0.003	-0.006
	(0.116)	(0.047)	(0.049)	(0.037)	(0.033)
Dummy			Year		
N			8073		
Numb. of IVs			520		
Hansen test(p-value)			0.19		
Arellano–Bond test for AR(1), p-value			0.000		
Arellano–Bond test for AR(2), p-value			0.331		

Notes: We conducted the instrumental variable estimation of Arellano and Bond (1991), based on a dynamic panel specification with firm fixed effects to estimate firm outcome equation (1) including firm investments in a firm outcome variable $y_{i,t}$. We used the lagged values of the firm covariates ($\mathrm{Firm}_{i,t-k}$, $k = 2, ..., 9$), the outcome variable ($y_{i,t-k}$, $k = 2, ..., 4$), and the termination variable ($\mathrm{CUT}_{i,t-k}$, $k = 2, ..., 8$) as instrumental variables. Parameter estimates are obtained by also using the bank leverage ratio ($\mathrm{WLEV}_{i,t-1}$) and bank exposure to the real estate industry in 1989 ($\mathrm{WEXP}^{\mathrm{Estate}}_{i,t-1}$) as instruments. Other independent variables are included in our estimation but not reported in the table. Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% levels of significance, respectively.

firm investment is not significant for the four lags of the termination variable, but still significant for the contemporaneous value. From these estimation results, we suggest that the bank-driven termination effect on firm investment lasts for no longer than one year. This implies that firms facing relationship terminations can obtain financing for investment by establishing new relationships or increasing borrowings within their existing relationships at least one year later.

1.4.4 Sorting Effects

As discussed in Subsection 1.1.4, we controlled for sorting effects of relationship terminations using firm fixed effects in the dynamic panel specification of firm investment. In this subsection, we demonstrate that our estimated termination effects are still robust even if we assume that the sorting effects could not be fully controlled by the firm fixed effects only. To this end, we directly weaken the

Table 1.13: Termination Effects with Different Weights in 2001–2005

	Past Years			Equal Weights	
	$w_{i,j,1997}$	$w_{i,j,1998}$	$w_{i,j,1999}$	All	Subsample
Dependent variable: INVEST					
Independent variable: CUT					
	0.182*	0.169*	0.241*	0.239**	0.183**
	(0.083)	(0.091)	(0.120)	(0.114)	(0.081)
Year × Ind. Dummy	✓	✓	✓	✓	✓
N	8126	8404	8714	9330	5471
Hansen test (p-value)	0.375	0.162	0.264	0.191	0.726
Arellano–Bond test for AR(1), p-value	0.000	0.000	0.000	0.000	0.001
Arellano–Bond test for AR(2), p-value	0.493	0.490	0.810	0.474	0.769

Notes: See Subsection 1.4.4 for definition of the five weighting variables: $w_{i,j,1997}$, $w_{i,j,1998}$, $w_{i,j,1999}$. For the equally-weighted variable shown in columns 5 (subsample), we estimate the firm investment equation based on the the subsample of firms whose number of lenders is above the median value (this median value is six) of all samples. We conducted the instrumental variable estimation of Arellano and Bond (1991), based on a dynamic panel specification with firm fixed effects to estimate firm outcome equation (1) including firm investments in a firm outcome variable $y_{i,t}$. We used the lagged values of the firm covariates, the outcome variable, and the termination variable as instrumental variables. Parameter estimates are obtained by also using the bank leverage ratio ($\mathrm{WLEV}_{i,t-1}$) and bank exposure to the real estate industry in 1989 ($\mathrm{WEXP}^{\mathrm{Estate}}_{i,t-1}$) as instruments. Other independent variables are included in our estimation but not reported in the table. *, **, and *** indicate 10%, 5%, and 1% levels of significance, respectively.

sorting effects in the weighting variable (4), $w_{i,j,t-1}$, which is defined as firm i's borrowing exposure to its borrowing bank j in the previous year $t-1$.

In our causal analysis, the endogeneity issue of the sorting effects involves using the weighting variable $w_{i,j,t-1}$ to construct the two instrumental variables, as expressed in (5) and (6). By definition, the sorting effects are weaken if the weighting variable is defined in a more distant relationship in the past and with a more equal weight. Given this insight, we take two approaches: one is using firm's exposure to its borrowing bank in a more distant year, such as $w_{i,j,1997}$ and $w_{i,j,1998}$, for the empirical analysis of period III from 2001 to 2005. The other is using a firm i's equally-weighted borrowing exposure to its all borrowing banks, defined more specifically as $w_{i,j,t-1} = w_{i,t-1}^{equal} = \frac{100}{\text{Number of Lenders at } t-1}$. For the equally-weighted variable, we also estimate the firm investment equation based on the the subsample of firms whose number of lenders is above the median value (this median value is six) of all samples, because the sorting effects would be more diluted as the number of lenders increases.

Table 1.13 reports estimation results based on the two instruments constructed with three weighting variables at fixed previous years 1997, 1998 and 1999, $w_{i,j,1997}$, $w_{i,j,1998}$ and $w_{i,j,1999}$ and the equally-weighted variables, $w_{i,t-1}^{equal}$. In this table, the fourth and fifth column show the result for all samples and the subsample, respectively. The estimated termination effect on firm investment is still significant and does not qualitatively change even if we use all the alternative weighting variables. This suggests that our estimated termination effects thus far are robust to a probable cause of the sorting effects in our empirical framework.

1.5 Conclusion

This paper exploits the characteristics of a matched sample that allows us to identify the terminations of bank–borrower relationships, thereby examining the effect of terminations driven by lending banks on the investment of borrowing firms. Using a matched dataset for Japanese lending banks and listed firms from 1991 to 2010, we obtain two substantive conclusions.

First, banks with larger exposures to the real estate industry during the bubble economy of the late 1980s were more likely to terminate their relationships in the early 2000s when the Japanese government obliged banks to dispose of their nonperforming loans promptly and relatively important relationships for borrowing firms were terminated. Such bank-driven terminations had about a one-year lasting effect on firm investment, such that a 10% decline in bank borrowings because of bank-driven terminations would decrease firm investment by 3.0%. While firm investment in the early 2000s increased by only 0.42% on average, the average impact of the bank-driven terminations was -1.03%. The impact of terminations on a firm's investment is then substantial and more significant, compared with the impact of changes in borrowings within continuing relationships. Therefore, terminations of bank–borrower relationships matter per se.

Second, this bank-driven termination effect is significant during the period when borrowing firms that faced termination had difficulty in immediately locating other financing sources for investment by establishing a new relationship or increasing borrowings within their existing relationships. Moreover, this tendency is more substantial for smaller firms facing severe asymmetric information problems. The early 2000s in Japan saw such dysfunction in the credit market.

These results provide us with an understanding of the extent to which search frictions in credit markets and the collapse of relation-specific assets would cause the problem of credit undersupply in a developed economy, thus creating rich implications for the design of regulation policy for banks. For example, if banks with impaired assets are more likely to terminate relationships and firms facing these terminations are forced to decrease investment, we may avoid such behavior by designing the regulation for excessive risk-taking by banks. We do think that understanding the magnitude of the bank-driven termination effect and its background mechanism is an effective step in considering a way to mitigate the credit undersupply.

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Chapter 2

Risk-Taking Channel of Unconventional Monetary Policies in Bank Lending

After the 2007–2008 financial crisis, the turmoil in the financial markets and contracting real economy led central banks in developed countries to lower their monetary policy rates effectively to zero. However, the zero lower bound of interest rates hindered the ability of central banks to maintain the inflation rate around their target levels or to stimulate the economy. To overcome this situation, central banks introduced unconventional policy measures such as purchasing long-term government bonds and commercial papers as well as introducing negative interest rates on central bank deposits.

Since the introduction of such unconventional monetary policies, a growing strand of the literature has empirically investigated their effects on asset markets and the real economy.[1] However, the existing literature does not fully examine how such policies affect the real economy in terms of the bank lending channel. In this study, we thus examine whether and how unconventional monetary policy affects bank lending behavior by providing micro-level evidence based on loan-level

[1]Previous studies of the effect of unconventional monetary policy have mainly used aggregate data as well as the vector autoregression (VAR) or event study methods. See, for example, Joyce et al. (2012) for a survey of empirical research on unconventional policy effects.

matched data on Japanese banks and their borrowing firms.

Concern about banks' risk-taking channels has risen given that the period leading up to the 2007–2008 financial crisis was characterized by low monetary policy rates and low inflation in developed countries. The literature on risk-taking channels has examined the link between banks' excessive risk-taking in lending and conventional monetary policy in the period before the crisis, during which central banks kept their policy rates at low levels to stabilize inflation and output.[2]

Recent theoretical studies demonstrate that a lower monetary policy rate plays a critical role in driving excessive leverage and risk-taking in lending to firms with higher credit risks (see Allen and Gale (2000, 2003, 2007), Adrian and Shin (2011), Acharya and Naqvi (2012), Diamond and Rajan (2012), Dell'Ariccia et al. (2014) and Martinez-Miera and Repullo (2017)).[3] In addition, recent evidence supports this theoretical prediction about the effect of conventional monetary policy (Maddaloni and Peydró (2011, 2013), Altunbas et al. (2014), Buch et al. (2014), Jiménez et al. (2014), Ioannidou et al. (2015), Dell'Ariccia et al. (2016)).[4]

This theoretical and empirical research warns that easing monetary policy encourages banks to lend more to firms with higher credit risks as well as stimulates the so-called credit channel (i.e., the conventional bank lending channel)

[2]While previous research has summarized the risk-taking channel in the context of credit risks, documenting that banks tend to make riskier loans when monetary policy rates are low, some empirical studies focus on financial intermediaries' search for yields mechanisms in the context of duration risk or mismeasurement of credit risks. See, for example, Becker and Ivashina (2015), Chodorow-Reich (2014), and Hanson and Stein (2015) for the empirical analyses of US financial intermediaries' search for yields under the Fed's low interest rate policy. In an international context, Bruno and Shin (2015) found that US monetary policy easing increases cross-border banking capital flows as well as the leverage of international banks.

[3]The Allen and Gale models elucidate the links among a lower monetary policy rate, credit booms, and asset price bubbles due to bank agency problems. Adrian and Shin (2011), Acharya and Naqvi (2012), and Diamond and Rajan (2012) showed the link between conventional monetary policy and excessive risk-taking when lending based on moral hazard problems. Dell'Ariccia et al. (2014) showed that the effect of changes in policy rates on banks' credit risk-taking depends on the endogenous response of banks' leverage to changes in policy rates; hence, the effect is ambiguous.

[4]See Maddaloni and Peydró (2011), Altunbas et al. (2014), Buch et al. (2014), and Dell'Ariccia et al. (2016) for empirical analyses using data from the United States. For a study of the risk-taking channel in the euro area and Spain, see Maddaloni and Peydró (2013) and Jiménez et al. (2014), respectively. Ioannidou et al. (2015) examined the credit risk-taking channel in Bolivia.

because of bank and firm balance sheet effects.[5] In contrast to previous research on banks' credit risk-taking under conventional monetary policy, we aim to uncover the channel through which unconventional monetary policy increases banks' credit risk-taking in lending.

This study contributes to the strand of the literature on monetary policy in two main aspects. First, we investigate the effects of monetary policy on risk-taking behavior based on unconventional monetary policy shocks that are carefully extracted and disentangled by using financial market data by taking into account their characteristics as a news shock. Second, we exploit bank-firm matched loan data in Japan, where various unconventional policies have been employed for over 15 years and have suffered from problems in the banking sector. Hence, the interaction effects between monetary policy and banks' risk-taking in Japan provide us with important policy implications, even for other economies that have conducted unconventional monetary policies since the 2008 financial crisis.

By using the Japanese bank-firm matched data, we find that a rise in the share of the unconventional assets held by the Bank of Japan (BOJ) increases lending to firms with a lower distance-to-default ratio from banks with lower liquid assets and a higher risk appetite. On the contrary, a monetary base shock of increasing the BOJ's balance sheet size does not have such heterogeneous effects. We also find that interest rate cuts stimulate lending to risky firms from banks with a higher leverage ratio and risk appetite.

The chief difficulty in identifying the extent to which unconventional policy affects bank lending is how to extract the exogenous shocks of such monetary policy. In this study, we thus focus on three types of shocks, namely short-term interest rate shocks, monetary base shocks, and composition shocks. Although previous studies have not fully disentangled the different effects of unconventional policies, it is implausible to consider that a single type of monetary policy shock is sufficient to describe the effects of unconventional policies on the economy.[6]

[5]See Bernanke and Blinder (1988, 1992), Kashyap and Stein (2000), and Jiménez et al. (2012) for banks' balance sheet effects. See Bernanke and Gertler (1995) for firms' balance sheet effects.

[6]Few studies have investigated the issue of disentangling multiple monetary policy shocks. For example, Campbell et al. (2012) showed that the forward guidance shocks of the Fed can be categorized into two types of monetary policy shocks, namely Delphic and Odyssean shocks.

Indeed, the changes in the balance sheet of the BOJ provide us with a leading case of unconventional monetary policy measures that have been introduced since the late 1990s. Figure 2.1 shows the year-on-year growth rate of the monetary base (calculated as the log-difference multiplied by 100 to show it on a percentage basis), the ratio of unconventional assets to total assets held by the BOJ and the policy interest rates (i.e., overnight call rates) from March 1999 to March 2015. This figure illustrates the massive growth in the monetary base in the early 2000s and decline in 2007, with another increase after the implementation of quantitative and qualitative monetary easing (hereafter, QQE) in 2013. We should also note a sharp increase in the ratio of risky assets to its total assets in the post-2013 period. In other words, the recent expansion of its assets appears different from that in the 2000s. Hence, Figure 2.1 suggests that using only one policy measure is insufficient to capture the effects of unconventional monetary policy.

Previous research has noted that disentangling the different effects of unconventional monetary policies is complicated. For example, the event study approach, which is often used to examine the impact of unconventional monetary policy, does not explicitly disentangle the effects of different policies because some measures are implemented at the same time. Even if we exploit financial market information by exploring a high-frequency dataset, this approach would be insufficient to disentangle the effects of different policies, as it does not directly map monetary policy tools onto surprise variables.

Furthermore, unconventional monetary policy shocks are a type of news shock. In other words, while central banks including the BOJ and Fed announce the schedule of the purchase of government bonds on a policy meeting day, the observable economic variable reacts to the change slowly (see Nakashima et al. (2017)).[7] Therefore, if we used only aggregate variables such as the monetary base

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Swanson (2015) also investigated the effects of unconventional monetary policy by disentangling large-scale asset purchase shocks from forward guidance shocks. In our study, building on the work of these two studies, we map different policy shocks onto different policy measures. Furthermore, we do not focus on only forward guidance shocks. See Section 2.2 for more details on our identification strategy.

[7]Nakashima et al. (2017) identified one type of conventional policy shock, namely short-term interest rate shocks, and two types of unconventional policy shocks, namely monetary base and composition shocks. They identified the two unconventional policy shocks as news shocks that

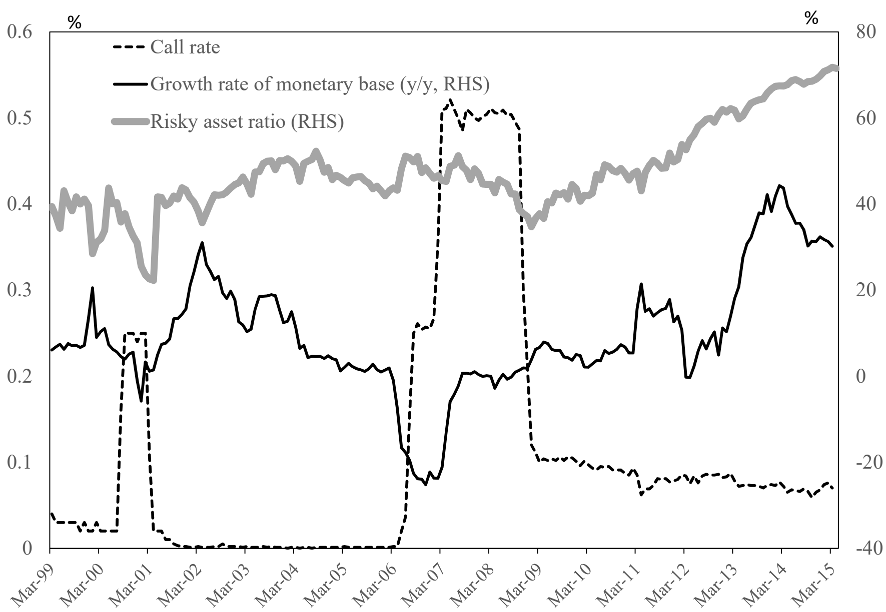

Figure 2.1: Monetary Base, Unconventional Assets and Call rate

Notes: The dark gray line indicates the ratio of unconventional assets to the total asset held by the Bank of Japan shown on a percentage basis. The black solid line indicates year-on-year growth rate of monetary base, which is calculated as the log-difference, shown on a percentage basis. The dotted line indicates the call rate in percentage on the left-vertical axis. Unconventional Assets include the exchange-traded fund (ETF), real estate investment trust (REIT), corporate bonds, commercial papers, long-term government bonds, and asset backed securities. Conventional assets include other assets such as short-term government bonds.

to analyze unconventional monetary policy effects, we would fail to identify how monetary policy shocks affect the economy. Moreover, as studies of news shocks have demonstrated, agents start to adapt their behavior immediately after news arrives.[8] Hence, we cannot identify the effect of such shocks if we focus on a change in aggregate variables only after a move in monetary policy measures has been observed.

To overcome these problems, we employ a two-step identification strategy for monetary policy shocks. We first construct the surprises arising in asset markets after monetary policy meeting days and then associate these surprises with monetary policy tools to identify monetary policy shocks. These policy shocks are not only plausible measures to address the effects of unconventional monetary policy, but also help us shed light on the differences among those measures. Thus, in this study, we investigate the effects of different measures by distinguishing the unconventional policies employed by the BOJ in the past 15 years.

Through our empirical analysis, we exploit a matched bank-firm dataset to disentangle the effects of monetary policy from the demand effects of each firm, in line with Jiménez et al. (2012, 2014), who used loan application data from the Spanish credit register. More specifically, in our main model, we control for the demand and supply effects by using double fixed effects, namely firm*year effects and bank*year effects. Thus, we examine the heterogeneous effects of unconventional monetary policy on bank lending, particularly focusing on the soundness of banks' balance sheets and their risk aversion.

By using Japanese data, our study illuminates the risk-taking channel of unconventional monetary policies, as this is a leading example of a developed economy with banking sector problems in addition to low growth and inflation rates. Since the collapse of the bubble economy in the 1990s, the heterogeneity of banks' behavior due to the soundness of their balance sheets has become a central issue in Japan (Peek and Rosengren (2005)).[9] In addition to banks' balance sheet prob-

best predict the future paths of the monetary base and the composition of the central bank's balance sheet.

[8]Uhlig (2004), Barsky and Sims (2011), and Kurmann and Otrok (2013) employed the structural VAR approach to identify news shocks about future technology, TFP.

[9]Peek and Rosengren (2005) found heterogeneous lending behavior across Japanese financial

lems, the Japanese economy from the 2000s was characterized by extremely low short-term interest rates and low inflation rates under the BOJ's unconventional monetary policy, and a growing number of studies have investigated the effects of such unconventional monetary policy on the economy. However, the heterogeneous effects of unconventional monetary policy in terms of banks' balance sheet soundness have not been fully studied, with the exception of some works such as Hosono and Miyakawa (2014) and Ono et al. (2016). Hosono and Miyakawa (2014) investigated the bank's balance sheet channel of monetary policy shocks by using Japanese firm-bank matched loan data and found evidence of the balance sheet channel. However, they did not extract the exogenous components of monetary policy measures or consider the nature of unconventional monetary policy shocks as news shocks, whereas we take these into account. Ono et al. (2016) showed that lower long-term yields stimulate bank lending by inducing portfolio rebalancing and easing capital constraints; however, they also did not explicitly identify unconventional monetary policy shocks.

To our knowledge, Jiménez et al. (2014) and Dell'Ariccia et al. (2016) are the only other studies that have examined the degree to which the relationship between monetary policy easing and credit risk-taking changes with bank capitalization by using a matched bank-firm dataset. Jiménez et al. (2014), for instance, showed that the negative relationship between interest rates and risk-taking in Spain is less pronounced for banks with relatively high capital, while Dell'Ariccia et al. (2016) showed that the negative relationship is more pronounced for those with high capital in the United States.[10] This previous research has focused only on the links among the monetary policy rate, bank capitalization, and bank risk-taking. In this study, however, we add to the body of knowledge on this topic by

intermediaries after the collapse of the bubble economy in the 1990s, motivated by balance sheet cosmetics. Furthermore, Caballero et al. (2008) suggested that such bank lending behavior distorted resource allocation in the economy by helping the survival of zombie firms, which would otherwise be insolvent.

[10]As in this study, Jiménez et al. (2014) used loan-level lender-borrower matched data and constructed a measure of risk-taking at the firm level. On the contrary, Dell'Ariccia et al. (2016) used confidential loan-level data on the internal ratings of US banks and prepared a risk-taking measure at the loan level. However, because the borrower's identify was not disclosed in their data, they did not control for firm characteristics.

analyzing whether and how conventional and unconventional policy easing affects banks' risk-taking depending on the soundness of their balance sheets.

The above empirical research on banks' risk-taking in lending has exploited variations in their financial fragility measured by using the leverage ratio or capital adequacy ratio. In other words, they have addressed the soundness of banks' balance sheets from the viewpoint of their liability structures. The other strand of the empirical literature on the credit channel has exploited variations in banks' access to liquidity, thereby demonstrating that those with more liquid assets are more likely to increase lending during monetary expansions (Kashyap and Stein (2000), Campello (2002)). Liquid assets, however, can also be associated with less lending if banks hold liquid assets including Japanese government bonds (JGBs) because of their motivation toward precautionary saving (Almeida et al. (2004), Dasgupta and Sengupta (2004)).[11] Therefore, the relationship between liquid assets and banks' risk-taking in lending is ex ante ambiguous. In addition, as Ono et al. (2016) pointed out, the intervention of the BOJ into a financial market such as JGBs has direct effects on returns and volatility in each market, which in turn induces a change in banks' investment behavior. Hence, banks' asset composition serves as a device to generate their heterogeneous responses to monetary policy shocks. We thus provide an insight into banks' risk-taking channels by addressing whether and how their asset and liability structures play a role in their credit risk-taking following monetary policy easing.

The remainder of the chapter proceeds as follows. Section 2.1 introduces the datasets we analyze. Section 2.2 discusses the exogenous components of monetary policy. Section 2.3 explains our empirical identification strategy. Section 2.4 discusses the results and Section 2.5 concludes. Appendix B.1 reports the estimation results of the probit model, which is used to calculate the inverse Mills ratio to control for the survival bias of bank-firm relationships. Appendix B.2 provides the estimation results for the double interaction effects of monetary policy and

[11] Dasgupta and Sengupta (2004) showed that, in a multiperiod setting, if firms anticipate being credit-constrained in the future, an increase in liquid balances may make their investment choices more conservative. Empirically, Almeida et al. (2004) found that firms tend to save more during recessions.

the bank risk variable. Appendix B.3 reports the estimation results for the probit model for firm bankruptcy to show that distance-to-default predicts the firm failure.

2.1 Data Sets: Loan-level Matched Data

The identification of the effects of unconventional monetary policy on bank lending is hampered by two crucial problems. First, banks with different levels of balance sheet soundness and of different sizes could face different levels of borrower demand; therefore, identifying credit supply without bank loans from different banks to the same borrower at the same time is impossible. Second, more affected banks may reject more borrowers when monetary policy is tightened, whereas less affected banks could provide more credit, thereby neutralizing the aggregate effects of any credit supply restrictions. Therefore, following Jiménez (2012, 2014), we use a loan-level dataset to overcome these problems.

Our loan-level data comprise a matched sample of Japanese banks and their borrowing firms listed in Japan. We construct our loan-level dataset based on the Corporate Borrowings from Financial Institutions Database compiled by Nikkei Digital Media Inc. This database collects information on the outstanding amounts of bank loans classified by maturity (long-term debt with a maturity of more than one year and short-term debt with a maturity of one year or less) and by bank. We then combine the Nikkei database with financial statement data on Japanese banks and their listed borrowing firms, also compiled by Nikkei Digital Media Inc.[12]

The Japanese banking sector experienced extensive M&A, business transfer, and divestiture activity in the late 1990s and early 2000s. As we faced difficulties collating loan-level data on bank mergers and restructuring, we record the dates on which bankruptcies and mergers took place in the Japanese banking sector. When a bank, included in our data, ceases to exist because of a bankruptcy or merger, firms stop considering that financial institution as a source of loans. In such cases,

[12] Although the fiscal year-end for Japanese banks is March 31, this is not necessarily the case for borrowing firms. When combining the Nikkei database with the financial statement data, we thus match bank-side information to borrower-side information in the same fiscal year.

Table 2.1: Average Number of Observations per Year

Number of observations	1990–1999	2000–2009	2010–2014
Firms	1,974	2,530	2,036
Banks	125	128	115
Relations	20,960	16,706	11,320

Notes: This table shows annual sample averages of the number of observations for borrowing firms, lending banks, and lending−borrowing relationships.

we adopted two procedures according to the existence of lending activities from the succeeding bank after the bankruptcy or merger: (1) if the firms that reported loans from the eliminated or consolidated bank before the event also reported loans from the succeeding bank, we consider those loans to be from the succeeding bank in order to calculate the loan growth rates of the succeeding bank; (2) on the contrary, if firms did not report any loans from the succeeding bank, we code the loan data as zero after the merger or consolidation (i.e., we consider the relationship was terminated). Thus, we carefully trace all changes in loans within each bank-firm relationship for all sample periods.

The loan-level dataset includes about 120 banks, 2,000 listed firms, and 17,000 relations per year for our sample period that runs from fiscal year 1999 to 2014, which covers March 1999 to March 2015 (see Table 2.1). Our dataset covers approximately 65% of all loans in the Japanese banking sector for our sample period. The number of observations is about 180,000. Table 2.2 provides the summary statistics for our loan-level matched data.

Table 2.2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	Number of Observations
Main Dependent Variable					
Growth Rate of Bank Loan	−5.2	55.9	−616.3	566.4	201975
Firm Variables					
Firm ROA	0.385	16.118	−1713.425	686.694	39951
Firm Size (in logarithm)	10.261	1.497	4.522	16.464	39951
Firm Book Leverage Ratio	57.767	21.983	0.913	1483.288	39951
Firm Distance-to-Default	49.481	117.678	−858.686	10484.758	37469
Real Estate Industry Dummy	0.04	0.196	0	1	39997
Bank Variables					
Bank ROA	−0.093	2.004	−45.091	15.328	2080
Bank Size (in logarithm)	14.736	1.27	12.079	19.087	2081
Bank Book Leverage Ratio	95.558	3.207	87.260	149.105	2081
Bank Market Leverage Ratio	95.755	2.573	73.438	99.869	1628
Bank Lending to Deposit Ratio	79.824	24.691	48.964	391.029	
Bank's Liquid Assets Ratio	15.9	5.7	1.4	43.2	1762
Bank's Government Bond Holdings Ratio	9.5	4.7	0.1	30.7	2069
Bank's Stock Holdings Ratio	2.041	1.409	0.092	9.926	2069

Table 2.2: Descriptive Statistics (continued)

Variable	Mean	Std. Dev.	Min.	Max.	Number of Observations
Main Dependent Variable					
High-risk High-return Bank Dummy	0.147	0.354	0	1	1956
Bank Non-performing Loan Ratio	3.83	3.101	0.13	53.726	1956
Bank Alternative Assets Ratio	3.448	2.824	0	23.936	1956
Relationship Variables					
Survival Dummy	0.806	0.395	0	1	258964
Lending Exposure of Bank	0.671	2.895	0.001	100	201975
Borrowing Exposure of Firm	15.466	17.403	0.001	100	201975
Relationship Duration (Year)	11.473	10.113	1	38	201975
Aggregate Variables					
CPI Change Rate	−0.19	0.682	−1.679	1.083	16
GDP Growth Rate	0.792	2.046	−4.184	3.404	16
Short-term Interest Shock	0.265	1	−1.251	2.737	16
Monetary Base Shock	−0.171	1	−1.757	2.382	16
Composition Shock	0.023	1	−1.724	1.908	16

Notes: Summary statistics are calculated from samples covering March 1999 through March 2015. The survival dummy equals one if a lending-borrowing relationship is terminated, otherwise zero.

2.2 Identification of Unconventional Monetary Policy Shocks

Identifying the effects of unconventional monetary policy requires the exogenous components of unconventional monetary policy, or monetary policy shocks.[13] In this section, we illustrate how monetary policy shocks can be extracted.

Cook and Hahn (1989), Wright (2012), Rogers et al. (2014), and Gertler and Karadi (2015) used high-frequency financial market data to identify monetary policy shocks, reasoning that a central bank's policy shocks are immediately reflected in asset prices as market participants' revise expectations after policy decisions are publicly announced.[14] If we can correctly obtain the revised expectations of participants in financial markets that are induced by a central bank's public statements or participants' surprises over a central bank's policy decisions, we can apply them as instrumental variables to extract monetary policy shocks from monetary policy measures. The relevant monetary policy measures are the overnight call rate (short-term interest rate), the monetary base, and the composition (risky assets ratio) of the central bank's balance sheet. We extract the monetary policy shocks from the three monetary policy variables.[15]

[13]Jiménez et al. (2012, 2014) examined how monetary policy affects bank lending in Spain. During the period analyzed, monetary policy rates were decided in Frankfurt, not Madrid, assuaging endogeneity in monetary policy. Ioannidou et al. (2015) examined the credit risk-taking channel of monetary policy in Bolivia. They used shifts in the U.S. federal funds rate as a proxy for exogenous changes in Bolivian short-term interest rates because Bolivian banking is effectively dollarized and the U.S. federal funds rate is determined independently of events in Bolivia.

[14]From this analytical viewpoint, recent empirical studies have used high-frequency daily trading data to assess the degree to which monetary policy affects asset prices. For example, Kuttner (2001), Cochrane and Piazzesi (2002), Gürkaynak et al. (2005a), Campbell et al. (2012), and Gertler and Karadi (2015) constructed policy surprises in federal funds or one-month euro-dollar futures that occurred on the Federal Fund Open Market Committee (FOMC) meeting dates. To examine the financial market's responses to exogenous monetary policy in Japan, Honda and Kuroki (2006) constructed policy surprises in three-month euro-yen futures that occurred on the BOJ's monetary policy meeting dates.

[15]Stock and Watson (2012) and Ramey (2016) surveyed in detail this empirical strategy to identify monetary policy shocks by using monetary policy surprises, namely changes in asset market prices, occurring after central bank public statements.

2.2.1 Monetary Policy Surprises

To quantify market participants' surprise, we examine changes in asset prices immediately before and after the BOJ's public statements. Previous studies that have employed a high-frequency identification strategy have focused on changes in short-term interest futures; on the contrary, we exploit all information on changes in major financial markets. To this end, we use principal component analysis and extract common factors as suggested by Bernanke et al. (2004) and Gürkaynak et al. (2005b). We adopt this approach because short-term rates have hardly changed since the BOJ introduced its unconventional monetary policy.

We examine policy surprises as the common factors underlying unanticipated changes in the major financial market variables following public statements. The principal component analysis of monetary policy on meeting day t is based on the following equation:

$$\mathbf{X_t} = \mathbf{\Lambda F_t} + \epsilon_\mathbf{t}, \tag{2.1}$$

where $\mathbf{X_t} = (x_{1t}, .., x_{nt})'$ denotes the vector of the n financial time series, $\epsilon_\mathbf{t}$ indicates the vector of the n idiosyncratic disturbance terms, $\mathbf{F_t}$ is the vector of l unobserved common factor, and $\mathbf{\Lambda}$ is a matrix of the coefficients identified as factor loadings. We aim to extract common factors $\mathbf{F_t}$ by using the factor model. We include 12 financial market variables x_{it} $(i = 1, .., 12)$: one futures rate (three-month euro-yen TIBOR futures), five yen interest swap rates (one, two, five, 10, 30 years), one short-term spot rate (three-month euro-yen TIBOR), two spot exchange rates on the Tokyo market (yen-U.S. dollar and yen-AUS dollar), two stock indexes (TOPIX and Nikkei JASDAQ), and banks' reserve deposits.

We calculate the differences in the seven interest rate variables and the log differences of exchange rates, stock indexes, and bank reserves as the percentages of the rate of change before and after public statements. More concretely, stock markets close at 3:00 p.m., and the BOJ usually convenes a press conference at 3:30 p.m. after the monetary policy meeting. When calculating changes in the 12 financial variables, we use the closing values on the day before the BOJ's public statements and the opening values on the next day. That is, for stock prices, exchange rates, and bank reserves, x_{it} is defined as follows:

$$x_{it} = \log(P_{it+1,open}/P_{it-1,close}) \times 100, \tag{2.2}$$

and for interest rates,

$$x_{it} = r_{it+1,open} - r_{it-1,close}, \tag{2.3}$$

where $P_{it+1,open}$ and $P_{it-1,close}$ indicate the opening values of exchange rates, stock indexes, and bank reserves on the day after a monetary policy meeting and the closing values on the previous day, respectively. $r_{it+1,open}$ and $r_{it-1,close}$ denote the opening and closing interest rates.

We preliminarily exclude the dates of the meetings at which the BOJ coordinated policy with the Fed, the European Central Bank, and the Bank of England as well as the dates on which the BOJ agreed its policy in response to the Tohoku earthquake on March 11, 2011. We did so because policy coordination and disaster response would contaminate the BOJ's policy effects.[16]

To select the number of common factors, we employ the information criteria proposed by Bai and Ng (2002) and Ahn and Horenstein (2013). These tests suggest that the principal components from the largest eigenvalues are three, and thus endorse adopting three common factors as the monetary policy surprises captured by the 12 financial variables. When constructing monthly data concerning policy surprises, we aggregate the two datasets of the three common factors if the BOJ's monetary policy meeting is held twice per month. By using the three principal components as instruments, that is, IV_1, IV_2, and IV_3, we extract the shocks from the conventional and unconventional monetary policy measures.[17]

[16] The BOJ meetings on September 18, 2008, September 29, 2008, and November 30, 2011 were held to coordinate policy. The meeting on March 14, 2011 agreed the BOJ's response to the Tohoku earthquake.

[17] The BOJ's monetary policy meeting is usually held once or twice per month. Each instrumental variable is more precisely defined as follows:

$$\mathrm{IV}_{kt} = \sum_{h_t \in H_t} \mathrm{IV}_{k h_t t},$$

where H_t indicates the set of days on which the monetary policy meeting is held in month t and

2.2.2 Exogenous Components of Monetary Policy

We use the three principal components as instrumental variables, IV_1, IV_2, and IV_3, to extract the shocks from the BOJ's monetary policies. More specifically, we regress the monthly changes in the three measures (overnight call rates, the monetary base, and the risky assets ratio) on these instrumental variables. This extraction method for measuring monetary policy shocks is in essence the same as the local projection method used to estimate the impulse responses of policy variables by exploited the forecast errors constructed from market-based expectations; that is, IV_1, IV_2, and IV_3 in our analytical framework (see Jordà (2005) for details on the local projection method). When constructing short-term rate shocks (i.e. overnight call rates shocks), we consider that they materialize immediately after the policy changes are announced (Nakashima et al. (2017)). Hence, we construct them as fitted values generated by the following regression:

$$\Delta\mathrm{SR}_t = (\beta_{1s} + \gamma_{1s} D_t)\mathrm{IV}_{1t} + (\beta_{2s} + \gamma_{2s} D_t)\mathrm{IV}_{2t} + (\beta_{3s} + \gamma_{3s} D_t)\mathrm{IV}_{3t} + \epsilon_{st}, \quad (2.4)$$

where ΔSR_t denotes the change in short-term rates in month t, IV_{kt} denotes the instrumental variables k in month t, and D_t denotes a dummy that takes 1 after April 2013, when the BOJ introduced QQE, and 0 otherwise. Including the dummy captures the possibility that our instrumental variables exert more effects on the economy because of the commitment and increased credibility of BOJ policy. We aggregate the exogenous components, namely the fitted values, for each year to construct the annual data for the short-term rate shocks.

Identifying the monetary base and composition shocks, each of which should be attributed to market participants' surprises at the BOJ's public statement about its policy decisions, is not a straightforward exercise. When the BOJ implements QQE, on its monetary policy meeting days, it only announces its target level of the BOJ current account balance, or the schedule of buying government bonds and risky assets such as ETFs and REITs. Hence, we can observe a gradual increase in the size of the central bank's balance sheet and a gradual change in its composition

$\mathrm{IV}_{kh_t t}$ denotes the principal components of the two-day changes in financial asset prices after these monetary policy meeting days.

after the monetary policy meeting.

This fact requires us to consider the monetary base and composition shocks to be news shocks. The market reaction, in effect, reflects an immediate prediction about the outcome of targets that will not be attained just after the policy meeting. In other words, even if the monetary base and risky assets ratio change immediately after meeting days, we cannot simply use those changes as unconventional monetary policy shocks (see also Nakashima et al. (2017)).[18]

Taking into account the contrast of the immediate and gradual responses of the asset markets and unconventional policy measures, we regress the monetary base and risky assets ratio on the lags of our instrumental variables. More specifically, we extract the exogenous components of the monetary base changes as the fitted values obtained by regressing the monthly growth rate in the monetary base on the three-month averages of the instrumental variables as follows:

$$\Delta \mathrm{MB}_t = \sum_{l=1}^{4} (\beta_{1ml} + \gamma_{1ml} D_t) \mathrm{IV}_{1t}^{l} + \sum_{l=1}^{4} (\beta_{2ml} + \gamma_{2ml} D_t) \mathrm{IV}_{2t}^{l} + \sum_{l=1}^{4} (\beta_{3ml} + \gamma_{3ml} D_t) \mathrm{IV}_{3t}^{l} + \epsilon_{mt}, \tag{2.5}$$

where IV_{kt}^{l} $(l = 1, .., 4)$ indicates the three-month average of instrumental variable k from month $t - 3l + 1$ to $t - 3(l - 1)$. D_t denotes a dummy that takes 1 after April 2013, when the BOJ introduced QQE, and 0 otherwise. The reason we include the three-month averages of the instruments rather than directly including their 12th-order lagged variables is that we aim to mitigate the problem of overfitting by reducing the number of instruments and R-squared values in this first-stage instrumental variable regression (Hansen and Kozbur (2014)). This equation shows that changes in the monetary base occur gradually during the year after the policy meeting, whereas markets immediately respond to policy changes and the instrumental variables capture such immediate market responses based on market participants' quickly revised expectations.

[18]As emphasized in Nakashima et al. (2017), when identifying shocks from unconventional monetary policies, one cannot employ a simple identification method through contemporaneous restrictions, such as in a recursive VAR.

As in the case of the monetary base, we extract the exogenous components of the composition changes as the fitted values obtained in the following regression:

$$\Delta \text{COMP}_t = \sum_{l=1}^{4} (\beta_{1cl} + \gamma_{1cl} D_t) \text{IV}_{1t}^{l} + \sum_{l=1}^{4} (\beta_{2cl} + \gamma_{2cl} D_t) \text{IV}_{2t}^{l} + \sum_{l=1}^{4} (\beta_{3cl} + \gamma_{3cl} D_t) \text{IV}_{3t}^{l} + \epsilon_{ct}, \tag{2.6}$$

where the risky assets ratio (COMP) is risky assets (long-term JGBs, ETFs, stock, REITs, commercial papers, and corporate bonds) divided by total BOJ assets.

We aggregate the fitted values obtained from the instrumental variable regression of the monetary base and risky assets ratio to construct annual data.

The exogenous component of the policy measures and their changes appear in Figure 2.2. The exogenous component of short-term rates plummeted in FY 2001 and FY 2008 when the BOJ lowered its policy rate following the collapse of the Internet bubble and the 2008 financial crisis, respectively. On the contrary, 2006 showed an increase in the exogenous components and the change in short-term rates when the BOJ began tapering QE. Our strategy of using monetary policy surprises as instrumental variables thus works well to capture shifts in the monetary policy stances of the BOJ, which is reflected to the short-term rates.

The monetary base substantially increased in 2013 when the BOJ increased its balance sheet to achieve its inflation target by introducing QQE. At the same time, the exogenous component for the monetary base increased dramatically, which implies that such a large expansion was surprising for financial markets. The exogenous components of the monetary base also increased in 2001 when the BOJ introduced QE to confront deflation. On the contrary, the 2006 decrease in the monetary base was relatively large, while the decrease in its exogenous components was modest. This finding suggests that financial markets somewhat anticipated the onset of tapering.

The exogenous component (i.e., fitted value) for the change in asset composition increased substantially in 2001, coinciding with a relatively large increase in the exogenous component of the monetary base. During this period, the BOJ bought more long-term bonds and changed its policy target from overnight call rates to its current account balance. The exogenous component also increased in 2013 after the launch of QQE when the BOJ again bought more long-term bonds and began buying risky assets such as REITs. Our exogenous components for the BOJ's asset composition capture changes in the BOJ's monetary policy scheme.

2.2.3 Monetary Policy Shocks

We should also note that Figure 2.2 shows that the BOJ employed different policies contemporaneously. For example, increases in the risky assets ratio often coincided with an expansion of the BOJ's balance sheet. Our method allows the exogenous components to correlate with each other, although correlation makes it difficult to understand how each shock affected bank lending.

To overcome this problem, we disentangle each monetary policy shock by using the Cholesky decomposition. We construct a variance-covariance matrix of the exogenous components (fitted value) and apply the Cholesky decomposition by standardizing their standard deviation as one. When computing the variance-covariance matrix, we arrange the exogenous components in the order of short-term rates, monetary base, and risky assets ratio, assuming the recursive determination of the policy rate, size of the BOJ's balance sheet, and its composition. This assumption aligns with the BOJ's aim of implementing QE and QQE.[19] As discussed above, changes in the three policy measures might correlate with each other. Therefore, we expect the composition and size shocks obtained via the Cholesky decomposition to differ from those in the original series.

Figure 3 shows the orthogonalized monetary policy shocks for the sample period. This figure highlights that the estimated policy shocks and corresponding exogenous components, namely fitted values, of the policy indicators do not necessarily move simultaneously in equal magnitude. Such a difference is clear in the

[19]Speaking on April 12, 2013, just after the BOJ introduced QQE, Governor Kuroda commented, "Consequently, it becomes important to determine not only how much liquidity to supply but also how to supply that quantity. Even with the same amount of liquidity, purchasing short-term T-Bills produces different effects than in the case where the Bank purchases other assets such as long-term JGBs and risk assets like exchange-traded funds (ETFs). Thus, it is important to work on two aspects of monetary easing, both in terms of quantity and quality."

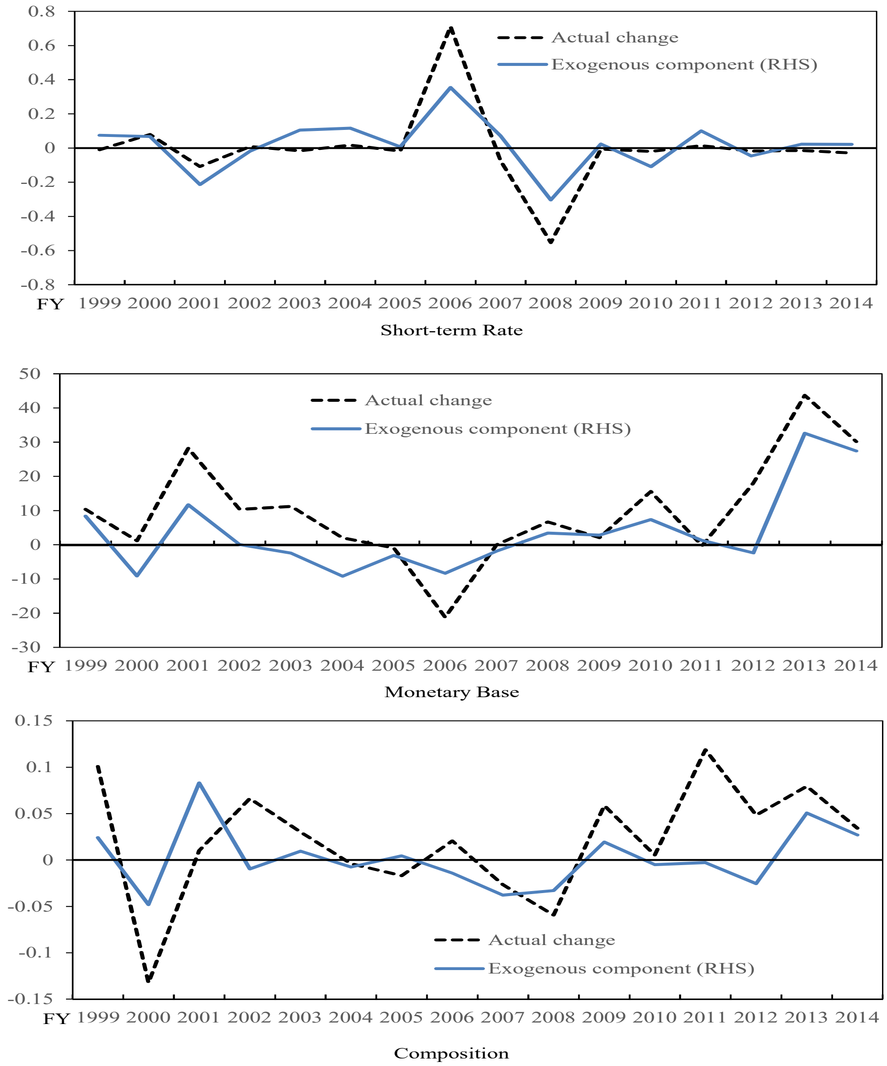

Figure 2.2: Exogenous Components of Monetary Policy Instruments

Notes: Exogenous components of short-term rates are obtained by regressing monthly changes in the short-term rates on unexpected contemporaneous monetary policy surprises, which are used as instrumental variables. These surprises are extracted as three principal components from prices and rates changes of twelve financial assets immediately before and after public announcements on monetary policy meeting days. Exogenous components of composition and monetary base are obtained by regressing monthly changes in risky asset ratio and monetary base on the k-quarter lagged monetary policy surprises ($k = 0, ..., 3$), respectively. Each series is summarized on a fiscal year basis.

changes in the risky assets ratio and composition shock after the BOJ introduced QQE in 2013. During QQE, the risky assets ratio rose but the BOJ's balance sheet also drastically increased. The Cholesky decomposition extracted the exogenous increase in the risky assets ratio, which is not explained by the increase in size.[20] In other words, the BOJ intentionally or unintentionally altered the composition of its balance sheet when adjusting its size. Hence, a small change in the exogenous component of the composition would not be identified as an independent composition shock. Rather, it would reflect only the monetary base shocks. Therefore, a negative composition shock in 2013 indicates that the increase in the composition in 2013 was insufficiently large to be identified as a composition shock. Orthogonalization allows us to examine how independent composition shocks affected bank lending.[21]

By using the policy shocks corresponding to each monetary policy indicator, the following sections analyze how unconventional monetary policy affected bank lending.

2.3 Econometric Model and Estimation Method

In this section, we introduce a loan-level specification of bank lending and then discuss the estimation method to investigate the effects of the monetary policy shocks.

2.3.1 Loan-level Specification of Bank Lending

To exploit our loan-level matched data fully, we employ a panel regression with double fixed effects, following Jiménez et al. (2012, 2014). In this specification, we control for the borrower and lender effects of unconventional monetary

[20] Note that the decomposition purely depends on the data, which reflect the policymaker's intention and market participants' perceptions of it. The results might change if the BOJ employs a new framework for monetary policy.

[21] A different approach to examine the effects of purchasing unconventional risky assets is to focus on the BOJ's share in each asset market. Li and Wei (2013) investigated the effects of QE in the United States by measuring the share of the Fed's holdings in the U.S. bond market. We disregard this strategy because we investigate the comprehensive effects of increasing the risky assets ratio on bank loans.

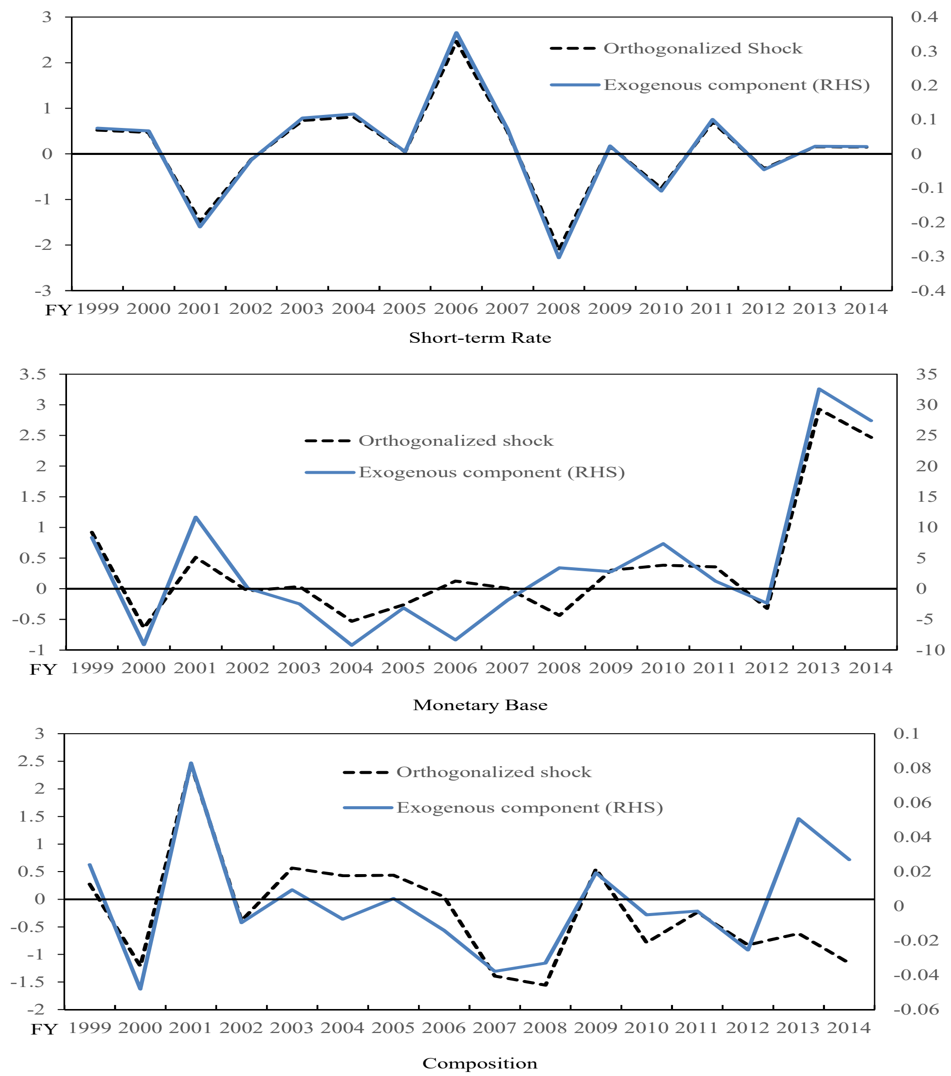

Figure 2.3: Monetary Policy Shocks

Notes: Short-term rate, monetary base, and composition shocks are obtained by implementing Cholesky decomposition on fitted values of those measures, which are obtained by using three monetary policy surprises as instrumental variables. Exogenous components of short-term rates are obtained by regressing monthly changes in the short-term rates on unexpected contemporaneous monetary policy surprises, which are used as instrumental variables. These surprises are extracted as three principal components from prices and rates changes of twelve financial assets immediately before and after public announcements on monetary policy meeting days. Exogenous components of composition and monetary base are obtained by regressing monthly changes in risky asset ratio and monetary base on the k-quarter lagged monetary policy surprises ($k = 0, ..., 3$), respectively. Each shock is summarized on a fiscal year basis.

policy, focusing on its heterogeneous credit "allocation" effects owing to the heterogeneity in banks' balance sheet risks.

Our baseline model with time-variant bank and firm fixed effects is specified as follows:

$$\Delta\text{LOAN}_{ijt} = \sum_{k=1}^{3}(\delta_k \text{FIRM}_{it-1} * \text{BANK}_{jt-1} * \text{MP}_{kt}) + \text{FirmFE}_{it} + \text{BankFE}_{jt} + \gamma' \text{CONTROL}_{ijt} + \epsilon_{ijt}. \quad (2.7)$$

where $\text{FIRM}_{\text{it}-1}$ is a risky firm indicator that takes one if firm i is categorized as one with high credit risk and zero otherwise. BANK_{jt-1} is a proxy for a bank's balance sheet risk, such as the leverage ratio and the liquidity ratio. FirmFE_{it} and BankFE_{jt} indicate the firm and the bank fixed effects, respectively. Both fixed effects are interacted with the year dummies, which control for the effects of monetary policy shocks through the borrower and lender factors. CONTROL_{ijt} denotes a vector of the other control variables including the triple interaction terms among a macroeconomic variable (or monetary policy shock), a firm variable, and a bank variable to control for the effects of interactions other than those relevant to our interest $\text{FIRM}_{it-1} * \text{BANK}_{jt-1} * \text{MP}_{kt}$. Note that this model does not include variables other than the triple interaction terms because the firm*year and bank*year fixed effects absorb those other variables such as the simple year dummies.

In Equation (2.7), we address only the heterogeneous policy effects on lending to risky firms ascribed to the heterogeneity in bank's risk compared with those to non-risky firms. This is because the firm*year and bank*year fixed effects absorb and control for the direct effects of monetary policy and the indirect effects of monetary policy through the firm's credit risks and the bank's balance sheet risks. Hence, we can define only the interaction effects involving the triple interaction terms. The first derivative with respect to a monetary policy shock is expressed as follows:

$$\frac{\partial \Delta\text{LOAN}_{ijt}}{\partial \text{MP}_{kt}} = \delta_k \text{FIRM}_{it-1} * \text{BANK}_{jt-1} + \text{others}_1,$$

where others_1 indicates the first derivatives of the other triple interaction terms with respect to the monetary policy shock. We should note that with these time-variant bank and firm fixed effects, we cannot estimate the average effects of the monetary policy shocks on bank lending because the time-variant fixed effect terms disappear when we take the derivative of them with respect to monetary policy shocks, although those fixed effects would absorb a large part of the average effects.[22]

When we further take the second derivative with respect to the bank risk variable, the first derivative reduces to the following second derivative:

$$\frac{\partial^2 \Delta\text{LOAN}_{ijt}}{\partial \text{MP}_{kt} \partial \text{BANK}_{jt-1}} = \delta_k \text{FIRM}_{it-1} + \text{others}_2, \tag{2.8}$$

where others_2 indicates the second derivatives of the other triple interaction terms with respect to the monetary policy shock and bank risk variable.

Finally, if we take the third derivative of the triple interaction term with respect to the monetary policy shock, and the bank and firm risk variables, we obtain the triple interaction effect as follows:

$$\frac{\partial^3 \Delta\text{LOAN}_{ijt}}{\partial \text{MP}_{kt} \partial \text{BANK}_{jt-1} \partial \text{FIRM}_{it-1}} = \delta_k. \tag{2.9}$$

By estimating the interaction effects, we identify the heterogeneous effects of monetary policy shocks MP_{kt} across the bank risk variable BANK_{jt-1} on lending to risky firms identified by FIRM_{it-1}. This coefficient has important policy implications as Jimenez et al. (2014) discussed. For example, suppose that larger bank and firm risk variables mean banks and firms with higher risks, respectively. Then, a positive triple interaction effect implies that a bank with higher risk is more likely to increase lending to risky firms compared with lending to non-risky firms in response to a monetary policy shock. In other words, regardless of whether the average effects of the monetary policy shock are positive or negative, the positive coefficient of the triple interaction term indicates that the share of lending to risky

[22] In Appendix B.2, we also show the estimation results for the double interaction effects with time-variant firm and time-invariant bank fixed effects, although our focus in this paper is on the triple interaction effect. For the estimation of the average effects, see Nakashima et al. (2017).

firms in the total loans of the bank with higher risk increases more than that for a bank with lower risk in response to the monetary policy shock.[23] Hence, the triple interaction effect captures the heterogeneous risk profile change in banks' portfolios across those with different degrees of balance sheet risk.

Our baseline model (2.7) with time-variant bank and firm fixed effects is an appropriate specification for examining the credit allocation effect of monetary policy because it allows us to control for bank-supply and firm-demand factors through the bank*year and firm*year fixed effects.

Monetary Policy Shocks and Interaction Terms Equation (2.7) has the interaction terms for the monetary policy shocks MP_{kt}. These interactions are the key variables explaining the extent to which unconventional monetary policy heterogeneously affects bank lending. MP_{kt} denotes one of the three monetary policy shocks, which we obtained from the Cholesky decomposition of the exogenous components of the monetary policy measures in Section 2.2. Accordingly, we can construct three double interaction terms for each of the bank risk variables with the monetary policy shocks, short-term interest rate shocks (SHORT), monetary base shocks (MB), and composition shocks (COMP). Hence we have three triple interaction effects ($\mathrm{FIRM}_{it-1} * \mathrm{BANK}_{jt-1} * \mathrm{MP}_{kt}$, $k = 1, 2, 3$) in the baeline model (2.7).

A short-term rate shock means that the BOJ's increase in nominal overnight call rates exceeded market expectations. Greater monetary base shocks mean accommodating shocks to the monetary base. The increase in composition shocks represents an increase in the ratio of the risky assets held by the BOJ.

Firm Credit Risks Jiménez et al. (2014) used a firm's history of defaulting on bank loans to measure the firm's credit risk in their matched lender-borrower

[23]This statement holds even if the double interaction effect of a monetary policy shock and the bank risk is negative. The negative double interaction effect means that a bank with higher risk decreases lending equally to risky and non-risky firms more than banks with lower risk do, in response to a monetary policy shock. Then, the positive triple interaction effect implies that banks with higher risk decrease loans to risky firms less than those to non-risky firms and this difference becomes larger as the bank becomes riskier. Therefore the share of risky lending for a riskier bank in its total lending increases more than that for a less risky bank. In other words, the triple interaction effect is a key factor to explain the allocation effects of monetary policy.

sample in Spain. In our matched lender-borrower sample in Japan, however, such loan default data are not available. We thus use distance-to-default as a proxy for firms' credit risk (FIRM_{it-1}) in Equation (2.7).[24]

Distance-to-default is theoretically derived from Merton's (1974) structural options pricing model. It allows us to incorporate information about a firm's equity, value, and volatility in a theoretically rigorous measure. Distance-to-default has substantial power to predict default and is widely used by banks to manage credit risk (Bharath and Shumway, 2008).[25] In fact, in Appendix B.3, we show the estimation results for the probit model for firm bankruptcy, which highlights that distance-to-default significantly predicts a firm's failure.

Distance-to-default is defined as follows:

$$DD = \frac{\ln\left(V_A/D\right) + \left(r - \frac{1}{2}\sigma_A^2\right)}{\sigma_A}, \tag{2.10}$$

where V_A denotes the market value of the borrowing firm, D denotes the book value of its liabilities, r indicates the risk-free rate, and σ_A indicates the volatility of firm assets. Distance-to-default can be interpreted as the expected standardized difference between the market value of the firm and the book value of its liabilities. If the difference is small (large), a firm is in danger of bankruptcy (healthy). A decrease (increase) in distance-to-default implies greater (lesser) credit risk.

We define the volatility of firm asset σ_A as $\sigma_A = \sigma_E \times V_E/V_A$, where the borrower's market value (V_A) is the sum of the market value of equity (V_E) and book value of total liabilities (D).[26] We calculate the market value of equity by

[24] We estimate a bankruptcy model of a firm and the results are shown in Appendix B.3. The result indicates that our firm risk variable, distance-to-default, provides explanatory power for a firm's bankruptcy.

[25] Empirical studies that use distance-to-default as a proxy for credit risk include Vassalou and Xing (2004), Gropp et al. (2006), Duffie et al. (2007), Gilchrist et al. (2009), Harada and Ito (2011), and Nakashima (2016).

[26] To compute distance-to-default, we must obtain two unobservable components: the market value of the firm's assets (V_A) and their volatility (σ_A). To this end, an iterative procedure is usually adopted to solve the two nonlinear equations derived from the Black–Scholes–Merton formula (Crosbie and Bohn (2003), Vassalou and Xing (2004)). Bharath and Shumway (2008) examined the accuracy of distance-to-default and suggested that its functional form, as expressed in Equation (5), matters for forecasting defaults rather than the solution of the two nonlinear equations (see Duffie et al. (2007)). Our calculation of distance-to-default follows their suggestion.

multiplying the stock price at the end of year $t-1$ by the number of shares. To estimate the volatility of equity (σ_E), we calculate the standard deviation for the market value of equity for the final month of a firm's fiscal year and express the estimated volatility as annual rates.[27] We use one-year JGBs for the risk-free rate (r).

We rank firms' credit risk by distance-to-default and construct a low distance-to-default indicator for the firm, (FLDD4_{it-1}), which takes one if firm i's distance-to-default at the end of fiscal year $t-1$ is less than the lowest quartile of all observations in the same fiscal year and zero otherwise. If the risk-taking channels of unconventional monetary policy exist, accommodating policy would increase bank loans to firms with higher risks belonging to FLDD4.

As discussed in the Introduction, studies of the credit risk-taking channel have examined lending to firms with high credit risks. In addition, as the Japanese banking crisis in the late 1990s and the 2008 financial crisis in the United States showed, the links among the real estate bubble, credit boom, and accommodative monetary policy have become a central issue to scholars and central bankers. To reveal how unconventional monetary policy affects bank lending to the real estate industry, we thus also use a real estate industry dummy (ESTATE) to indicate firm risk instead of low distance-to-default firms, FLDD4.

Banks' Financial Risks We assess the financial soundness and risk aversion of banks by the asset and liability structures of their balance sheets. The liability structure captures financial stability and risk preferences, which relate to debt burdens and leverage. The asset structure also reflects the soundness of a bank's balance sheet as indicated by access to liquid assets (i.e., liquidity con-

[27]More specifically, we calculate the annualized estimated volatility of the market value of equity as follows:

$$\sigma_{E,it} = \sqrt{\frac{1}{20-1} \times \sum_{k=d(t)-19}^{d(t)} \left(ret_k - \overline{ret_{d(t)}}\right)^2} \times \sqrt{240},$$

where $d(t)$ denotes the last trading day of firm i's fiscal year t, ret_k denotes the daily rate of change in equity valuation, and $\overline{ret_{d(t)}}$ is the average rate of change in equity valuation during the previous 20 days.

straints) in addition to its risk preference. Therefore, we choose a bank risk variable (BANK_{jt-1}) by considering the characteristics of a bank's asset and liability structures.

Previous studies of Japanese bank lending ascribe its heterogeneity to the soundness of banks' balance sheets, particularly measured by capital assets ratios (Gan (2007), Watanabe (2007), Peek and Rosengren (2005), and Caballero et al. (2008)) or non-performing loan ratios (Hoshi (2001) and Ogawa (2003)).[28] With regard to a bank's capitalization or liability structure, we measure balance sheet soundness as the market leverage ratio indicating the insufficiency of a bank's equity capital (BMLEV_{jt-1}) in our models. The reason that we use the market capital measure, and not book capital measures such as the regulatory capital ratio and the book leverage ratio, is partly because book capital measures do not reflect the actual conditions of Japanese banks' capitalization (Fukao (2008) and Hoshi and Kashyap (2010)), and partly because theoretical studies emphasizing the role of bank capital in its risk-taking deal with the bank capital in market value terms since market value responds to shocks including monetary policy shocks and thus is more appropriate for analyzing the relationship between banks' leverage and portfolio risks (e.g. Calomiris and Wilson (2004), Adrian and Shin (2011), and Dell'Ariccia et al. (2014)). We define the market leverage ratio as $100 \times \frac{\text{Book Value of Debt}}{\text{Market Value of Equity } + \, Book\ Value\ of\ Debt}$, where the market value of equities is defined as the product of the stock price per issue and the number of stock issues. In addition to the market leverage ratio, we use the non-performing loan ratio (BNPL_{jt-1}) as a proxy for balance sheet soundness. The non-performing loan ratio is the ratio of reported non-performing loans to total loans.

The coefficient of the triple interaction terms, for example, for the composition shocks ($\text{FIRM}_{it-1} * \text{BMLEV}_{jt-1} * \text{COMP}_t$), would have a positive value if a risk-taking channel exists because a positive coefficient implies that a bank with low capitalization is likely to increase more (or decrease less) lending in response

[28]According to Gan (2007) and Watanabe (2007), insufficient capital assets ratios after the bubble economy burst forced Japanese banks to reduce domestic lending. By contrast, Peek and Rosengren (2005) and Caballero et al. (2008) suggested that such unhealthy banks increased lending to low quality firms owing to balance sheet cosmetics, thereby distorting the allocation of credit in Japan.

to an accommodating composition shock than one with high capitalization.[29] On the contrary, if the response to such a shock equally affects risky lending from both banks with low and high equity capital, the coefficient would be zero, indicating that there does not exist a risk-taking channel depending on heterogeneities in banks' leverage.

Some empirical studies establishing the credit supply effects of monetary policy have emphasized heterogeneities in banks' holdings of liquidity assets (e.g. Kashyap and Stein (2000) and Hosono (2006)) in terms of asset structure. Hence, to investigate whether unconventional monetary policy induces heterogeneous risk-taking behavior by banks depending on their asset structure, we also include interaction terms for the liquid assets ratio (BLIQ_{jt-1}), monetary policy shocks, and a firm risk variable. The liquid assets ratio is defined as the ratio of the sum of a bank's cash, deposits, loans outstanding in the call market, and JGB holdings to total book assets. As discussed in the Introduction, the coefficient of the interaction terms for liquid assets and the other components of bank assets with monetary policy shocks could be positive or negative.

In addition to the liquid assets ratio, we use the ratio of JGB holdings to total assets (BJGB_{jt-1}) and stock holdings (BSTOCK_{jt-1}). Most JGBs are held by Japanese financial intermediaries, including banks, which also have substantial holdings of corporate stocks. Given the fact that the BOJ intervened aggressively in these two financial markets under QQE, the exposures to these two financial markets would directly affect the lending stance of Japanese banks through banks' reach for yields behavior and the change in the soundness of banks' balance sheets.

Furthermore, Japanese banks increased JGB holdings to raise their capital adequacy ratio when they promoted the write-off of non-performing loans in the early 2000s. Hence, banks' investments in JGBs not only become a main source of banks' profits but also reflect their risk aversion. Therefore, a high JGB holdings ratio for a bank implies i) larger capital gains owing to lower interest rates, ii) a low risk appetite, and iii) fewer liquidity constraints. Thus, the coefficient of the triple interaction terms for JGB holdings would also be negative and positive, as

[29]We should note that positive monetary base and composition shocks mean monetary policy easing, while a positive short-term rate shock indicates tightening.

discussed for the liquid assets ratio.

A similar argument can be applied to the bank's stock holdings. For example, if an increase in banks' capital gains, which stemmed from the BOJ's intervention into the stock markets by increasing its risky asset ratio, stimulates risky lending, a bank with a higher stock holdings ratio would responds more significantly to the easing policy. If this is the case, the interaction term with composition shocks would have a positive coefficient. On the contrary, if the accommodating policy induces reach for yields behavior by less risky banks, banks with a lower stock holdings ratio may increase riskier lending, which suggests a negative estimate for the triple interaction effects for composition shocks. Again, the coefficient of the triple interaction term with the bank's stock holdings would be both negative and positive.

By including the asset component variables, we can thus pin down the channel through which unconventional monetary policy affected bank lending most actively. Accordingly, we investigate not only the interaction effects for banks' liquidity constraints, but also those for risk-taking attitude and the direct effects through the financial markets.

Other Control Variables We also include other control variables in the panel regression models. In particular, in addition to the main triple interaction variables ($\text{FIRM}_{it-1} * \text{BANK}_{jt-1} * \text{MP}_{kt}$) in Equation (2.7), we include the other eight triple interaction terms among a macroeconomic variable (or monetary policy shock), the firm risk variable, and a bank variable as the control variables. As macroeconomic variables, we use the growth rates of the consumer price index and the real GDP from year $t-2$ to $t-1$. As a variable for firm risk, we use the distance-to-default ratio. As a bank variable, we use bank size (BSIZE_{jt-1}) and return on assets (BROA_{jt-1}) to control for profitability and size. The bank size is defined as a logarithm of the bank's total assets and the return on assets is the ratio of net profits to the book value of total assets. More concretely, the eight triple interaction terms include two interaction terms composed by one of the two macroeconomic variables, a firm's distance-to-default and a bank risk variable, to control for the interaction effects with the macroeconomic environment.

The remaining six interaction terms are included to disentangle the interaction effects of monetary policy with the other bank characteristics. Each of them is constructed by interacting one of the three monetary policy shocks, one of the two bank control variables (ROA or SIZE), and the firm risk variable. In sum, we have eight interaction terms to control for the other interaction effects.

Finally, in Equation (2.7), all the bank and firm variables and their double interaction effects with monetary policy shocks are excluded because the effects are absorbed by the bank*year and firm*year fixed effects. Thus, we have only the triple interaction terms for the model.

2.3.2 Correcting for Survivorship Bias

Our matched lender-borrower sample is based on a continuation of the lending relationship. According to the literature on relationship banking, the continuation of a bank-firm relationship depends on both the bank's and the firm's characteristics (Ongena and Smith (2001) and Nakashima and Takahashi (2017)). In other words, we must address the survivorship bias that may arise from non-random assortative matching between banks and firms.

To correct for survivorship bias, we employ Heckman's (1979) two-stage regression technique. The first stage is a probit regression of whether the relationship survived; the second stage is a regression of the loan growth based on the estimation method discussed above. To the extent that the credit allocation is a two-step process in which a bank first decides whether to lend and then decides how much to lend, the selection model provides an insight into both decisions.

Our probit regression includes the one-period lags of the firm's leverage ratio (FLEV_{it-1}), return on assets (FROA_{it-1}), interest coverage ratio (FICR_{it-1}), and size (FSIZE_{it-1}). To control for the firm-level attributes, we also include dummy variables for the industries to which firms belong. Bank characteristics contain the one-period lags of the bank's leverage ratio (BLEV_{jt-1}), return on assets (BROA_{jt-1}), and size (BSIZE_{jt-1}). In addition to the bank-firm characteristics, our probit regression includes the one-period lags of bank j's lending exposure to firm i (EXPL_{ijt}), firm i's borrowing exposure from bank j (EXPB_{ijt-1}), and the duration of the relationship between lender i and its borrowing firm j (DURAT_{ijt-1}) as relationship factors.[30] We run the probit regression for the continuation of bank-firm relationships and then run the second-stage regression of the bank lending equation with the inverse Mills ratio. To take into account the possibility that the coefficients of the variables in the probit model are time-varying, as pointed out by Nakashima and Takahashi (2017), we conduct a rolling estimation of the probit model year by year.

The details of the estimation results are shown in Appendix B.1. On the basis of the probit model, we calculate the inverse Mills ratio and include it to control for survival bias in the bank loan model in the second stage regression.

2.4 Estimation Results

In this section, we discuss the estimation results to provide insight into the extent to which unconventional monetary policy affects Japanese banks' credit risk-taking in lending.

2.4.1 Risk-taking Channel

In this subsection, we report the estimation results of Equation (2.7) to investigate the extent to which the firm's credit risk matters for banks' risk-taking in response to expansionary monetary policy shocks. Table 3 reports the estimation results obtained by using the FLDD4 dummy variable as the risky firm indicator and the bank market leverage ratio as the bank risk variable.

The triple interaction term composed of the interest rate shocks, bank's market leverage ratio, and bottom one-quarter of firms as ranked by distance-to-default (SHORT $*$ BCAP $*$ FLDD4) has a significantly negative estimate. This result indicates that the short-term rate shocks strongly encourage risk-taking by highly risky banks with relatively high leverage ratio.

[30] Borrowing exposure is calculated as bank j's loans to firm i as a percentage of the total loans to firm i, while lending exposure is calculated as firm i's loans from bank j as a percentage of the total loans from bank j.

The triple interaction term with the monetary base shocks (MB) is estimated to be insignificant, suggesting that these monetary base shocks do not have heterogeneous effects on bank lending in terms of bank capital and firm credit risks.

The composition shocks (COMP) have insignificant estimates of their triple interaction term with the bank's market leverage ratio (BCAP) and risky firm dummy (FLDD4).

In addition, note that the inverse Mills ratio has significantly positive estimates, implying that survivorship bias exists in such a way that we would obtain biased estimates for the parameter coefficients without including this ratio.[31]

Summing up, conventional policy easing by lowering short-term interest rates leads to a rise in credit from highly leveraged banks to risky firms compared with those from low leveraged banks, while quantitative easing by expanding the monetary base and qualitative easing by increasing the risky assets ratio do not.

Heterogeneous Effects of Bank Assets In this subsection, we explore the heterogeneous effects derived from the composition of bank assets. In particular, we address the interaction effects of banks' liquid assets and monetary policy shocks on lending by estimating Equation (2.7). Furthermore, we use other variables related to the main asset components of banks, namely JGBs, and corporate equity as a bank risk variable, to investigate the background mechanism of the effects of monetary policy shocks.

Banks' Liquid Assets The estimation results shown in column (1) of Table 4 are obtained by including the triple interaction terms (MP$*$BLIQ$*$FLDD4) of each policy shock, the bottom one-quarter of firms by distance-to-default, and the liquid assets ratio in Equation (2.7) as another bank risk variable instead of the triple interaction effects for the bank market leverage ratio.

Table 4 shows that the interaction term with the bank's liquid assets ratio (SHORT$*$BLIQ$*$FLDD4) does not have a significantly negative estimate, implying that banks with more liquid assets are unlikely to increase lending to riskier firms

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[31]

Table 2.3: Estimation Result of Baseline Bank Lending Model

	Baseline
Dep. Variable: $\Delta LOAN$	(1)
Monetary policy shocks	
SHORT*BMLEV*FLDD4	-0.260*
	(0.151)
MB*BMLEV*FLDD4	0.222
	(0.229)
COMP*BMLEV*FLDD4	0.0342
	(0.172)
Impact of a 1 St. Dev. change in a monetary policy shock on lending to risky firms from highly versus lowly leveraged banks (1 St. Dev. difference)	
Decrease in short-term rate	0.5%
Macroeconomic variables	
GDP*BMLEV*FLDD4	-0.185*
	(0.0987)
CPI*BMLEV*FLDD4	-0.254
	(0.333)
Other control variables	
Inverse Mills Ratio	0.473***
	(0.0214)
SHORT*BROA*FLDD4	-0.708
	(0.771)
MB*BROA*FLDD4	0.182
	(1.056)
COMP*BROA*FLDD4	-1.193
	(0.844)

Table 2.3: Estimation Result of Baseline Bank Lending Model (continued)

	Baseline
Dep. Variable: $\Delta LOAN$	(1)
SHORT*BSIZE*FLDD4	-0.278
	(0.223)
MB*BSIZE*FLDD4	-0.0335
	(0.235)
COMP*BSIZE*FLDD4	-0.738***
	(0.228)
Firm * Year fixed effect	✓
Bank * Year fixed effect	✓
N	169851

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. Robust standard errors are in parentheses. As the dependent variable, we use the first log-difference of the outstanding amount of bank loan multiplied by 100 for expression in percentage terms. This table shows the estimation results of the model with firm∗year and bank∗year fixed effects. Each variable denotes a triple interaction term comprised of monetary policy shocks (or macroeconomic variable), bank covariates, and firm covariates. MB, COMP, and SHORT indicate monetary base, composition and short term interest rates shocks, respectively. Increases in MB and COMP indicates increases in the monetary base and risky asset ratio held by the Bank of Japan, respectively. An increase in SHORT means an increase in short term interest rates. BMLEV indicates bank market leverage ratio. FLDD4 indicates the low distance-to-default firm dummy, where distance-to-default at the end of fiscal year $t-1$ is lower than the lowest quartile of all observations in the same fiscal year. Inverse Mills Ratio is multiplied by 100 and included in the independent variables following Heckman's bias correction procedure to correct for the survival bias of a relationship in our dataset. We excluded certain variables from our second stage estimation such as a firm's borrowing exposure from a bank as including these variables did not change our estimation results significantly.

compared with banks with less liquid assets in response to a short-term rate shock.

Furthermore, the monetary base shocks do not have heterogeneous effects on bank lending in terms of the bank's liquidity. Column (1) of Table 4 indicates that the coefficient of the triple interaction term for the monetary base shocks, bank liquidity, and firm risk (MB $*$ BLIQ $*$ FLDD4) has an estimate that is not significantly different zero.

The triple interaction term for the composition shock (COMP $*$ BLIQ $*$ FLDD4) has a significantly negative estimate, indicating that banks with a lower liquid assets ratio lend more to risky firms in response to the composition shocks. This result suggests that the composition shocks lead to risk-taking behavior by risky banks. Table 2.4 also provides the magnitude of the interaction effect by showing that a one standard deviation difference in the liquid asset ratio means a 0.5 percentage point higher increase in risky loans compared to non-risky loans, which is comparable to the effect of the market leverage ratio as shown in Table 2.3.

Table 2.4 summarizes our findings that the composition shocks are prone to stimulate lending from banks with lower liquid assets ratios.

Banks' JGB Holdings Ratio To investigate further which components of liquid assets determine the heterogeneous effects on lending, we include the bank's JGB holdings ratio (BJGB) instead of the liquid assets ratio as the bank risk variables.

The estimation result shown in column (2) of Table 2.4 indicates that the triple interaction effect for the short-term rate shocks, the bank's JGB holdings ratio, and firm risk (SHORT $*$ BJGB $*$ FLDD4) is estimated to be negative but insignificant. The triple interaction effects for the monetary base and composition shocks also have negative estimates although they are not significantly different from zero.

Corporate Stock Holdings Ratio We next include the triple interaction effect for the bank's stock holdings ratio, a monetary policy shock, and the firm risk variable (MP $*$ BSTOCK $*$ FLDD4) to address the direct channel through

Table 2.4: Estimation Results with Bank Assets

Dependent Variable: $\Delta LOAN$			
	(1)	(2)	(3)
Liquid Assets			
SHORT*BLIQ*FLDD4	0.0112		
	(0.0489)		
MB*BLIQ*FLDD4	0.0133		
	(0.0621)		
COMP*BLIQ*FLDD4	-0.0862*		
	(0.0477)		
Impact of a 1 St. Dev. change in a monetary policy shock on lending to risky firms from banks with **low versus high liquid assets ratio** (1 St. Dev. difference)			
Increase in composition	0.5%		
JGBs			
SHORT*BJGB*FLDD4		-0.0306	
		(0.0699)	
MB*BJGB*FLDD4		-0.0310	
		(0.0651)	
COMP*BJGB*FLDD4		-0.0970	
		(0.0693)	

Table 2.4: Estimation Results with Bank Assets (continued)

Dependent Variable: $\Delta LOAN$			
	(1)	(2)	(3)
Stocks			
SHORT*BSTOCK*FLDD4			-0.271
			(0.173)
MB*BSTOCK*FLDD4			0.271
			(0.281)
COMP*BSTOCK*FLDD4			0.263
			(0.192)
N	176181	186909	186909
Firm * Year fixed effect	✓	✓	✓
Bank * Year fixed effect	✓	✓	✓

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. Robust standard errors are in parentheses. The dependent variable, the first log-difference of the outstanding amount of bank loan, is multiplied by 100 for expression in percentage term. This table shows the estimation results of the model with firm∗year and bank∗year fixed effects. Each variable indicates a triple interaction term comprised of monetary policy shocks, bank covariates and firm covariates. $\mathrm{MB_t}$, $\mathrm{COMP_t}$, and $\mathrm{SHORT_t}$ indicate monetary base, composition and short term interest rates shocks, respectively. Increases in $\mathrm{MB_t}$ and $\mathrm{COMP_t}$ indicates an increase in monetary base and risky asset ratio held by the Bank of Japan, respectively. An increase in $\mathrm{SHORT_t}$ means an increase in short term interest rates. BMLEV indicates the bank market leverage ratio. BJGB, and BSTOCK denote Japanese government bond holdings ratio and stock holdings ratio to the bank's total assets, respectively. FLDD4 indicates the low distance-to-default firm dummy, where distance-to-default at the end of fiscal year $t-1$ is smaller than the lowest quartile of all observations in the same fiscal year. Inverse Mills Ratio is multiplied by 100 and included in the independent variables following Heckman's bias correction procedure to correct for the survival bias of a relationship in our dataset. In the second stage estimation, we include inverse Mills ratios and the following eight control variables of the triple interaction terms in our model: two interaction terms—one comprised of the change rate of GDP, the bank leverage ratio, and the low distance-to-default firm indicator and the other comprised of the change rate of CPI, the bank market leverage ratio, and the low distance-to-default firm indicator—with six triple interaction terms, each of which is comprised of one of three monetary policy shocks, one of the bank size and ROA, and the risky firm indicator . The estimated coefficients are not reported in the table as the estimation results are not quantitatively different from those shown in Table 2.3.

stock markets, in which the BOJ has purchased a substantial amount of ETFs under QQE.

Column (3) in Table 2.4 shows the estimation results, illustrating that none of the interaction terms with the stock holdings ratio is significantly different from zero. From this result, we can infer that the main direct channel through which monetary policy shocks affected bank lending differently was not stock markets. However, we should note that this exercise only examined direct effects through the stock holdings. In other words, other paths such as those via the soundness of firms' balance sheets by increasing the firms' capital were not taken into account.

Monetary Policy and the Real Estate Industry In this subsection, we reveal the extent to which unconventional monetary policy affects bank lending to the real estate industry. Therefore, we use the real estate industry dummy variable, ESTATE, as a firm risk indicator instead of low distance-to-default firms, FLDD.

Column (1) of Table 2.5 shows that none of the triple interaction terms composed of the monetary policy shocks, banks' market leverage ratio, and the real estate industry dummy have significant estimates.

Following previous studies (Hoshi (2001), Ogawa (2003)) that have found that the growth rates of loans to real estate industry by Japanese banks are associated with their non-performing loan ratios, we use non-performing loans as the bank risk variable instead of the bank leverage ratio. Column (2) of Table 2.5 indicates that the triple interaction term including the short-term interest rate shocks and bank's non-performing loan ratio (SHORT$*$BNPL$*$ESTATE) has a significantly negative estimate, while the other interaction effects are not significant. These estimation results imply that monetary policy easing by lowering short-term interest rates causes banks facing higher non-performing loans to increase lending to real estate firms more than non-real estate firms compared with those with low non-performing loan ratios. This finding provides the policy-relevant implication that conventional policy easing by lowering short-term rates boosts lending in the real estate industry by financially fragile banks, which might ultimately destabilize the banking system. Furthermore, this increase is not directly associated with the bank's JGB and stock holdings ratios because the interaction effect for the short-term rate shock, the JGB holdings ratio (or the stock holdings ratio), and the real estate industry firm dummy is not significant.[32]

2.4.2 Insight into a Bank's Risk-taking in Lending

Our estimation results have thus far shown that the three types of monetary policy measures (i.e., monetary policy rates, the monetary base, and the risky assets ratio) affect a bank's lending behavior differently. Here, we discuss some of the insights of the monetary policy effects on a bank's risk-taking in lending by showing additional estimation results of the models where other bank variables serve as a proxy for banks' risk preference.

Short-term Rate Shocks and Bank's Risk-taking Even under the extremely low interest rate regime of unconventional monetary policy, lowering monetary policy rates induces banks with higher leverage ratios to lend more to firms with high credit risk. One possible explanation for such an effect is that lower short-term rates ease banks' capital constraints by increasing their capital gains through the increases in prices of their assets. Another route of the effect related to banks is reach for yields behavior, which may arise because banks seek higher yields from securities holdings and lending (i.e., the existence of "yield-oriented" banks) as pointed out by Stein (2013). This type of investor has an incentive to increase current yields for institutional or accounting reasons. This tendency can drive banks to invest more in assets and lending that bear higher yields and risks, and it would actualize when the yields of their investment assets and JGBs decrease due to lower monetary policy rates. We examine these two channels, namely the effects of increasing capital and reach for yields behavior, using different bank risk variables instead of the market leverage ratio.

First, we should note that the heterogeneity in banks' government bond holdings does not have an interaction effect with the short-term rate shock as shown in Table 2.4. This fact implies that the heterogeneity in the size of the capital gains

[32] The estimation results for the coefficient on the triple interaction effects of the JGB and stock holding ration are not reported in Table 2.5.

Table 2.5: Estimation Results with the Real Estate Industry Dummy Variable

Dep. Variable: $\Delta LOAN$	(1) BANK= BMLEV	(2) BANK= BNPL
Monetary policy shocks		
SHORT*BANK*ESTATE	-0.385	-1.223**
	(0.398)	(0.559)
MB*BANK*ESTATE	-0.599	0.859
	(0.613)	(0.877)
COMP*BANK*ESTATE	0.636	0.211
	(0.516)	(0.629)
Macroeconomic variable		
GDP*BANK*ESTATE	-0.438*	-0.0816
	(0.250)	(0.327)
CPI*BANK*ESTATE	-0.122	-0.355
	(0.897)	(0.900)
N	169851	173048
Firm * Year fixed effect	✓	✓
Bank * Year fixed effect	✓	✓

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. Robust standard errors are in parentheses. This table shows the estimation results of the model with firm∗year and bank∗year fixed effects, where the first log-difference of outstanding amount of bank loan (multiplied by 100 to be expressed in percentage) is used as a dependent variable. The first and second columns specify the estimation result with the bank market leverage ratio (BMLEV) and bank non-performing ratio (BNPL), respectively as a bank risk variable. MB, COMP, and SHORT indicate monetary base, composition and short term interest rate shocks, respectively. An increase in MB and COMP indicate an increase in monetary base and risky asset ratio held by the Bank of Japan, respectively. An increase in SHORT indicates an increase in short term interest rates. FLDD4 indicates the low distance-to-default firm dummy, where distance-to-default at the end of fiscal year $t-1$ is smaller than the lowest quartile of all observations in the same fiscal year. Inverse Mills Ratio is multiplied by 100 and included in explanatory variables following Heckman's bias correction procedure to correct the survival bias of a relationship in our dataset. In the second stage estimation, we include inverse Mills ratios and the six triple interaction terms in our model, each of which is composed of one of monetary policy shocks, one of the bank size and ROA, and the risky firm indicator. The estimated coefficients are not reported in the table.

brought about by the monetary policy shock does not explain the heterogeneity in the risk-taking behavior by banks in response to the shock.Put differently, the results in Table 2.4 suggest that the channel through which conventional monetary policy mitigates banks' capital constraint by increasing capital gains due to low interest rates would not be a main driving factor for the risk-taking effects of conventional monetary policy.

Alternative Assets Ratio To address further why lowering short-term rates stimulates lending from risky banks to risky firms, we also use an indicator of banks with a high alternative assets ratio, $\mathrm{BHO}_{\mathrm{t}-1}$, as a bank risk variable instead of the bank leverage ratio and estimate the triple interaction effects. The alternative assets ratio is defined as the ratio of the sum of other securities and derivative holdings to total assets.[33]

The indicator for banks with a high alternative assets ratio is a dummy variable that takes one if the bank's alternative assets ratio is higher than the highest tertile of the samples in each year. The high other assets ratio indicator serves a proxy of the risk-taking attitude of banks to off-balance sheet activity and the tendency of banks to seek higher yields in the low interest rate environment. The estimation result shown in Table 2.6 indicates that the triple interaction effect of short-term rate shocks, the high other assets ratio dummy, and the firm risk variable ($\mathrm{SHORT} * \mathrm{BHO} * \mathrm{FLDD4}$) has a significantly negative estimate. This result implies that lowering the short-term rate increases risky lending from banks with a higher other assets ratio more than that from less risky banks. In other words, it suggests short-term rate shocks can stimulate reach for yields behavior by risky banks.

High-Risk High-Return Portfolio We also examine whether banks with higher risk appetite tend to increase credit to risky firms in response to monetary policy shocks using the risk profile of their loan portfolio. In portfolio management, a bank with high risk appetite would prefer a bank loan portfolio that has

[33]The exposure to the derivative contracts is used to capture off-balance sheet derivative trading activity in the existing literature. For example, Hagendorff et al. (2016) use the log of the ratio of derivative contracts held for trading over total assets to capture the riskiness of banks. Furthermore, Elul and Yeramilli (2013) point out that this is associated with the bank's risk management.

Table 2.6: Estimation Results with High Alternative Assets Ratio Bank Dummy

	(1)
Dep. Variable: $\Delta LOAN$	
Monetary policy interaction terms	
SHORT*BHO*FLDD4	-1.321**
	(0.583)
MB*BHO*FLDD4	0.783
	(0.733)
COMP*BHO*FLDD4	-0.234
	(0.609)
N	187168
Firm * Year fixed effect	✓
Bank * Year fixed effect	✓

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. Robust standard errors are in parentheses. The dependent variable, the first log-difference of outstanding amount of bank loan, is multiplied by 100 to be expressed in percentage. This table shows the estimation results of the model with firm$*$year and bank$*$year fixed effects. Each variable indicates a triple interaction term comprised of monetary policy shocks (or macroeconomic variable), bank covariates and firm covariates. MB, COMP, and SHORT indicate monetary base, composition and short term interest rate shocks, respectively. An increase in MB and COMP indicate an increase in monetary base and risky asset ratio held by the Bank of Japan, respectively. An increase in SHORT indicates an increase in short term interest rates. BHO indicates the high alternative assets ratio bank dummy, where the bank's ratio of the other securities and derivatives holdings to total assets in year $t-1$ is bigger than the highest tertile of all observations in each year $t-1$. FLDD4 indicates the low distance-to-default firm dummy, where distance-to-default at the end of fiscal year $t-1$ is smaller than the quartile of all observations in the same fiscal year. Inverse Mills Ratio is multiplied by 100 and included in the independent variables following Heckman's bias correction procedure to correct the survival bias of a relationship in our dataset. In the second stage estimation, we include inverse Mills ratios and the following eight control variables of the triple interaction terms in our model: two interaction terms—one comprised of the change rate of GDP, the high alternative assets bank indicator, and the low distance-to-default firm indicator and the other comprised of the change rate of CPI, the high alternative assets ratio bank indicator, and the low distance-to-default firm indicator—with six triple interaction terms, each of which is comprised of one of three monetary policy shocks, one of the bank size and ROA, and the risky firm indicator. The estimated coefficients are not reported in the table.

higher expected returns, but is exposed to higher volatility. Given this insight, we construct an indicator of a bank that has a higher return on lending and a higher volatility of the return. More concretely, we construct a dummy variable of banks with high returns and high risks, $\mathrm{BHRHV}_{\mathrm{t-1}}$, which takes one if the bank's lending returns, defined as the ratio of its interest received from all its loans to its total bank loans, is larger than the highest tertile in year $t-1$ and the volatility of the returns on bank loans from year $t-5$ to $t-1$ is larger than the median of all banks in year $t-1$, and zero otherwise. Then, we use the high-risk, high-return portfolio bank dummy as a bank risk indicator instead of the bank leverage ratio.

The estimation results in Table 2.7 show a significantly negative estimate for the triple interaction term for the short-term rate shock (SHORT$*$BHRHV $*$FLDD4) and a significantly positive estimate for the composition shocks (COMP$*$ BHRHV $*$FLDD4), indicating that banks with higher returns on loans and their volatility are more likely to increase loans to risky firms in response to a lowering short-term rate shock and a positive composition shock. Considering that risk and return have a trade-off relationship in a standard portfolio choice problem, this finding suggests that a short-term rate and a composition shock encourage banks with higher risk appetite to take more credit risks.

Monetary Base Shocks and Bank's Risk-taking On the contrary, the monetary base shocks do not have heterogeneous effects in terms of the firm's credit risk interacted with the banks' balance sheet and risk preference as shown in Tables 2.4 to 2.7. However, this does not exclude the possibility of its affecting bank lending homogeneously. In fact, in Appendix B.2, we show the estimation result of the double interaction effects of the monetary policy shocks and bank leverage, which indicates that an easing monetary base shock would increase lending from a highly leveraged bank more than that from a low leveraged bank. This result concurs with the finding of Baba et al. (2006) that the BOJ's unconventional policy prevented increases in risk premiums in financial markets, which helped facilitate the funding of Japanese banks. In the context of credit allocation toward risky firms, we find no risk-taking channel of the monetary base shock.

Table 2.7: Estimation Results with the Bank Dummy for High Return and High Risk Portfolio

	(1)
Dep. Variable: $\Delta LOAN$	
Monetary policy interaction terms	
SHORT*BHRHV*FLDD4	-2.154*
	(1.183)
MB*BHRHV*FLDD4	-0.229
	(0.949)
COMP*BHRHV*FLDD4	1.596**
	(0.744)
N	187168
Firm * Year fixed effect	✓
Bank * Year fixed effect	✓

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. Robust standard errors are in parentheses. The dependent variable, the first log-difference of outstanding amount of bank loan, is multiplied by 100 to be expressed in percentage. This table shows the estimation results of the model with firm∗year and bank∗year fixed effects. Each variable indicates a triple interaction term comprised of monetary policy shocks (or macroeconomic variable), bank covariates and firm covariates. MB, COMP, and SHORT indicate monetary base, composition and short term interest rate shocks, respectively. An increase in MB and COMP indicate an increase in monetary base and risky asset ratio held by the Bank of Japan, respectively. An increase in SHORT indicates an increase in short term interest rates. BHRHV indicates the high-risk high-return bank indicator, where the bank's return on lending in year $t-1$ is bigger than the median and the volatility of the return from t-5 to t-1 is bigger than the highest tertile of all observations in each year $t-1$. FLDD4 indicates the low distance-to-default firm dummy, where distance-to-default at the end of fiscal year $t-1$ is smaller than the quartile of all observations in the same fiscal year. Inverse Mills Ratio is multiplied by 100 and included in the independent variables following Heckman's bias correction procedure to correct the survival bias of a relationship in our dataset. In the second stage estimation, we include inverse Mills ratios and the following eight control variables of the triple interaction terms in our model: two interaction terms—one comprised of the change rate of GDP, the high-risk high-return bank indicator, and the low distance-to-default firm indicator and the other comprised of the change rate of CPI, the high-risk high-return bank indicator, and the low distance-to-default firm indicator—with six triple interaction terms, each of which is comprised of one of three monetary policy shocks, one of the bank size and ROA, and the risky firm indicator. The estimated coefficients are not reported in the table.

Composition Shocks and Bank's Risk-taking Composition shocks lead to an increase in bank loans from banks with low liquid assets ratios and high risk appetite to high risk firms as shown in Tables 2.4 and 2.7. One of the mechanisms of such an effect is that a composition shock increases the values of banks' assets by lowering risk premiums, which eases banks' liquidity constraints and induces the heterogeneous effects of monetary policy.

To further address the mechanism that banks with higher risk appetite increase lending to risky firms, we use the loan to deposit ratio as a bank risk variable instead of the bank leverage ratio. The loan to deposit ratio of a bank is defined as the ratio of the bank's total loans to deposit. We should note that Japanese banks basically do not reject deposits from their customers and the deposit is classified as a stable debt for banks. In particular, under a zero lower bound constraint of deposit interest rates, Japanese banks cannot not fully control for the amount of deposits. Hence, this ratio reflects the bank's risk taking attitude toward bank loans as well as its lending opportunity, compared to their deposits.

As shown in Table 2.8, the triple interaction effect of the composition shocks, the bank's loan to deposit ratio, and the low distance-to-default firm indicator is estimated to be significantly negative, while the other triple interaction effects for short-term rate shocks and monetary base shocks are not significantly different from zero. This finding suggests that the composition shocks stimulate lending behavior by banks that are taking more risks in lending in terms of the balance between the stable debt and lending loans. The finding supports that the composition shocks increase risky lending from banks with higher risk appetite, as demonstrated in Tables 2.4 and 2.7.

Policy Implications We find a clear distinction among the different monetary policy shocks. For conventional shocks, we find evidence that they stimulate reach for yields behavior by risky banks by lowering interest rates and forcing them to invest in other assets than JGBs. Similar to conventional shocks, the composition shocks encourage risk-taking behavior by banks with low liquid asset ratios and high risk appetite. On the contrary, monetary base shocks do not have heterogeneous effects on risky lending in terms of the leverage and liquidity of their

Table 2.8: Estimation Results with Loan to Deposit Ratio

	(1)
Dep. Variable: $\Delta LOAN$	
Monetary policy interaction terms	
SHORT*BLD*FLDD4	0.00578
	(0.0100)
MB*BLD*FLDD4	-0.00543
	(0.0116)
COMP*BLD*FLDD4	0.0137*
	(0.00749)
N	173203
Firm * Year fixed effect	✓
Bank * Year fixed effect	✓

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. Robust standard errors are in parentheses. The dependent variable, the first log-difference of outstanding amount of bank loan, is multiplied by 100 to be expressed in percentage. This table shows the estimation results of the model with firm∗year and bank∗year fixed effects. Each variable indicates a triple interaction term comprised of monetary policy shocks (or macroeconomic variable), bank covariates and firm covariates. MB, COMP, and SHORT indicate monetary base, composition and short term interest rate shocks, respectively. An increase in MB and COMP indicate an increase in monetary base and risky asset ratio held by the Bank of Japan, respectively. An increase in SHORT indicates an increase in short term interest rates. BLD indicates the bank's loan to deposit ratio. FLDD4 indicates the low distance-to-default firm dummy, where distance-to-default at the end of fiscal year $t-1$ is smaller than the quartile of all observations in the same fiscal year. Inverse Mills Ratio is multiplied by 100 and included in the independent variables following Heckman's bias correction procedure to correct the survival bias of a relationship in our dataset. In the second stage estimation, we include inverse Mills ratios and the following eight control variables of the triple interaction terms in our model: two interaction terms—one comprised of the change rate of GDP, the loan to deposit ratio, and the low distance-to-default firm indicator and the other comprised of the change rate of CPI, the loan to deposit ratio, and the low distance-to-default firm indicator—with six triple interaction terms, each of which is comprised of one of three monetary policy shocks, one of the bank size and ROA, and the risky firm indicator. The estimated coefficients are not reported in the table.

assets, and banks' risk preference.

Our finding of the heterogeneous effects of conventional monetary policy shocks on bank lending are in line with the finding of Jiménez et al. (2014), which showed that lowering short-term rates increases risky lending by banks with low capital, using Spanish loan registration data when interest rates are well above the effective zero lower bound. Moreover, we extend their finding by illustrating that even in an extremely low interest rate environment, short-term rates have a substantial effect on a bank's risk-taking behavior.

In addition, the composition shocks and monetary base shocks have different effects, although they are not distinguished well in the literature. One explanation of why the composition shocks alter the behavior of banks with low liquidity and high risk appetite is that they interpret those shocks as a signal that the central bank is playing a backstop role in banks' funding and risky asset markets (Li and Wei (2013), Bauer and Rudebusch (2014), Bekaert et al. (2013)). This signal induces a decline in risk premiums and the volatility of risky assets.[34] Although whether this signaling effect affects banks heterogeneously in terms of risky lending is not theoretically obvious, we find empirical evidence that this is the case: in other words, the composition shocks allow risky banks to take more credit risks than non-risky banks.

On the contrary, increasing the monetary base did not have heterogeneous effects on risky lending by risky banks, partly because it did not have such a strong signaling effect. The reason why the monetary base shocks did not have effects on risky lending would be that the exchange of money and government bonds did not have a substantial impact on the expected values of risky assets. On the contrary, changing the composition of the central bank's assets had a direct signal on the stance of monetary policy, which results in the risk-taking by risky banks.

As QE and QQE policy is designed to lower the risk premiums of risky assets such as stocks, we may conclude that unconventional policy easing by changing

[34]Bauer and Rudebusch (2014) pointed out that the decline in Treasury yields following asset purchase programs might also reflect investor perceptions that monetary policy is to remain accommodative for a longer period than the market previously expected. Bekaert et al. (2013) found that lax monetary policy decreases risk aversion and uncertainty about stock prices and the former effect is stronger using the VIX.

the composition ratio of conventional and unconventional assets has the expected effect. However, the resultant distortion in risky asset markets encourages the moral hazard of high risk appetite banks (Adrian and Shin (2011), Jiménez et al. (2014)). Considering our findings, central banks should thus guard against underestimating these side effects of unconventional monetary policy.

In particular, although banks would charge higher interest rates on lending to risky firms, they would be insufficiently large to make up for the credit risk that they take. As discussed in Section 2.3 (see also the result shown in Appendix B.3), the firm risk variable, distance-to-default, significantly affects the probability of the firm bankruptcy. However, if we calculate the interest gap following Caballero et al. (2008) and regress the interest gap on the low distance-to-default dummy, the coefficient is estimated to be insignificant as shown in Table 2.9.[35] This result suggests that higher credit risk or lower distance-to-default is not necessarily associated with higher interest payments.[36] We should note that our dataset only includes total interest rates on a firm's total debts. Hence, we cannot conduct a detailed loan-level analysis of interest rates as we did for outstanding amounts of loans. However, the result suggests that risky banks are likely to increase risky lending to exploit only a marginal increase in yields that would not cover the credit risk that they bear. Again, our findings urge policymakers to pay special attention to the side effects of monetary policy in terms of the credit risk-taking channel.

2.5 Conclusion

In this study, we investigated the effects of unconventional monetary policy on bank lending, using a bank-firm matched dataset in Japan from March 1999 to

[35]The interest rate gap for a firm is defined as the difference between the firm's actual interest payment and the hypothetical lower bound, which is normalized by the total amount of the firm's borrowing. Total borrowing is calculated as the sum of the outstanding amount of commercial paper, corporate bonds, and bank borrowing. The hypothetical lower bound of interest rate payments in year t is the extremely advantageous rate, which is calculated by using the prime rates for short-term borrowing in year t, the average prime rate for long-term bank borrowing from $t-4$ to t, and the minimum rate of convertible bonds issued between $t-4$ and t.

[36]Using the distance-to-default instead of its dummy variable does not change the result qualitatively.

Table 2.9: Estimation Result for Interest Rate Gaps Regression

	(1)
Dependent Variable:	Interest Rate Gap_t
FLDD4	-0.00110
	(0.00141)
Number of observations	35440

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. Standard errors are in parentheses. The dependent variable is the firm's interest rate gap (GAP) calculated by following Caballero et al. (2008). The independent variables consist of the year dummies and the low distance-to-default indicator. The indicator takes one if the firm's distance-to-default is lower than the quartile of samples in each year. The regression model is as follows,

$$GAP_{it} = \beta FLDD4_{it} + YearFE_t + e_{it}, \tag{2.11}$$

where e_{it} denotes a disturbance term. Using the firm's distance-to-default instead of its dummy variable does not change the result qualitatively. Including other control variables such as industry dummies and other firm covariates does not change result qualitatively.

March 2015. From the presented findings, we can draw three conclusions about banks' risk-taking channel under unconventional monetary policy. First, under an extremely low interest rate regime, lowering short-term interest rates induces banks with higher leverage ratios and higher risk appetite to lend more to firms with high credit risk owing to search for yields behavior, which occurs because of lower yields to maturity.

On the contrary, the QE policy of expanding the BOJ's balance sheet does not have heterogeneous effects on risky lending in terms of bank leverage and risk appetite, which implies that the risk-taking channel of the monetary base shocks was not effective.

Finally, qualitative easing through the purchase of risky assets induces banks with low liquid assets and high risk appetite to increase credit to firms with high credit risks; that is, the bank's risk-taking channel works under qualitative easing via banks with high risk appetite. Unlike conventional monetary policy easing, however, unconventional monetary policy does not directly change current short-term rates. Rather, it causes a signaling effect in which the central bank commits to decreasing risk premiums and expected short-term rates, thereby promoting banks with lower liquid assets (i.e., those with higher risk appetite) to take more credit risks.

2.6 Acknowledgments

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Chapter 3

Bank Loan Supply Shocks and the Real Economy: The Case of Japan

The 2008 financial crisis emphasized the incompleteness of financial markets by enabling researchers and policy makers to reacknowledge the roles of the financial sector as an amplifier and an origin of adverse shocks. However, as developed economies have experienced several financial crises prior to 2008, investigating the role of financial markets in a real ecoMinistry of Public Management nomy is not a recent issue. One of most influential financial crises prior to 2008 was the Japanese banking crisis that occurred following the collapse of the bubble economy in the 1990s.[1] Indeed, due to the poor performance of the Japanese economy in the past 20 years, the 2008 crisis provoked the discussion whether other developed economies such as the United States were facing the risk of "Japanization"; in other words, the possibility that the economy would experience prolonged downturn periods similar to that of Japan after 1990s was vigorously argued in the United States and Europe.[2]

[1]In the 1980s, the Japanese economy enjoyed a high growth rate of approximately 4%, although this marks a slow down from its 1970s era rate. After the bubble economy burst, it declined to 1.5% in 1990s, and remained at approximately 1% throughout the first half of the 2000s.

[2]On December 11, 2011, for example, in an article titled "Is America Going the way of Japan," New York Times discussed the risk that the American economy would experience after 2008.

This view of economies is based on the hypothesis that the slow growths of the Japanese economy were mainly caused by its malfunctioning financial system. However, identifying credit supply shocks is a complicated task because many other factors, such as aggregate demand shocks to the whole economy, affect both demand and supply of credits. Because of this difficulty in identifying credit supply shocks, the debate is ongoing concerning the extent to which they affected the real economy and whether the malfunctioning credit market was a main determinant of low growth rates in this so-called "lost two decades" period.

This study contributes to the continuing discussion by using Japanese business survey data, "Tankan," and employing the methodology proposed by Bassett et al. (2014) in order to overcome the identification problem.[3] I investigated the extent to which fluctuations in Japan's real economy can be explained by exogenous loan supply shocks, thereby drawing three main conclusions.

First, I show that a negative loan supply shock significantly decreases GDP, but the contribution is not economically substantial; bank loan supply shocks contribute approximately 7% to the GDP fluctuations. Second, I show that during the late 1990s financial crisis, bank loan supply shocks were attributable to the economy's contraction. I find that in 1998, without bank loan supply shocks, GDP growth rates would have remained positive and its decline in 1999 would have been half of the realized outcome. The effects of a negative bank loan supply shock in the crisis starting from the late 1990s crisis were significant, even compared to those in the 2008 crisis. Third, I find that the economy in a zero lower bound environment is more vulnerable to an adverse supply shock as theoretical literature predicts; in a zero lower bound environment, bank loan supply shocks contribute to about 10% of GDP fluctuations. This paper contributes to the strand of literature on the study of credit supply shocks by using a consistent data spanning three decades, rather than picking arbitrary periods. To my knowledge, this is first study to use and adjust Tankan survey to estimate the real effects of bank loan supply shocks in Japan over a three decade period.

However, the authors believed that the possibility was low for the United States to experience a similar situation faced by the Japanese economy in 1990s after the collapse of its bubble economy.

[3]See Section 3.1 for the detail of the Tankan survey.

The Tankan survey is conducted by the Bank of Japan to understand business conditions, which has some advantages in investigating loan supply shock effects over other dataset used in previous studies. First, it covers a long time period during which the constraint of a zero lower bound on nominal interest rates was binding. The study of the effect of bank loan shocks in Japan provides some useful insights for other economies as the Japanese economy has been in a zero lower bound environment for more than 10 years in total. Previous theoretical studies demonstrated that an economy in a zero lower bound environment shows different dynamics compared with those in a non-zero lower bound environment.[4] After the 2008 financial crisis, not only Japan but also many other developed countries, faced a zero lower bound on nominal interest rates. However, few studies have investigated how and whether the effect of bank loan supply shocks on the real economy changes in a zero lower bound environment. Therefore, this study examines the different behavior of a real economy after being hit by bank loan supply shocks in a zero lower bound environment. Furthermore, Tankan offers quarterly firm-survey data that began in the 1970s and has been compiled in a consistent manner.[5] Compared to other studies such as ones that utilized annual data of bank balance sheets, the quarterly Tankan data provide us more comprehensive and detailed understandings over the development of economy.

Several studies have used Tankan survey data to identify bank loan supply shocks. Among them, Brunner and Kamin (1995) used the Tankan data from 1970 through 1989 to show that bank loan supply shocks have small effects on the real economy. Motonishi and Yoshikawa (1999) used the Tankan survey to estimate the investment function of Japanese firms. They focused on the decline in firm investment that occurred during the 1990s, finding evidence of a credit crunch in the late 1990s. However, no studies have investigated the role of bank loan supply shocks through the 1990s and 2000s, using the Tankan data.

[4] See e.g., Eggertsson and Woodford (2003).

[5] In the Tankan survery, there is a discontinuity between the data through December 2003 and those after March 2004 because of the change in the size classification and revisions to sample enterprises. However, this study is not affected by the size classification. Furthermore, the conclusions in this study does not change even if I use the original time-series that is available through the March 2009 survey.

Regarding the identification issue of loan supply shocks, we employed the strategy of Bassett et al. (2014). They used bank-level data from the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS) and adjusted for banks-specific characteristics and loan demand factors in order to extract loan supply shocks from SLOOS. Thereafter, they aggregated the SLOOS panel data to investigate the relationship between bank loan supply shocks and the real economy, finding that the loan supply shocks would explain approximately 20% of the real GDP fluctuation in the past 20 years.

The approach employed by Bassett et al. (2014) has two distinct features from previous methodologies. First, they adjusted for the other factors related to loan demand shocks, whereas previous studies used the SLOOS itself as sole data for loan supply shocks. Controlling for the other factors such as macroeconomic conditions mitigates the omitted variable problem.[6] Second, their use of panel data enables them to control for bank-specific characteristics to identify bank loan supply shocks.[7] Following the strategy of Bassett et al. (2014), I use industry-level Japanese Tankan survey data to exploit the benefits of their methodology.

This paper addresses the effect of bank loan supply shocks by identifying them in a consistent and simple manner over three decades, contributing the continuing debate about reasons for the lost two decades. Previous literature found some evidence that a negative shift of the bank loan supply function, often called as "credit crunch" or "capital crunch," caused low growths of investment and GDP in the late 1990s in Japan. Among others, Woo (2003) showed that the capital adequacy ratio significantly affected the bank loan growth rate after 1997 using bank-panel data. Focusing on the real estate bubble in the 1980s, Gan (2007a) also demonstrated that declining land prices in the 1990s dampened bank lending and firm investment using Japanese loan-level panel data. However, these previous studies focused only on the late 1990s banking crisis. Significantly fewer

[6]Indeed, Bassett et al. (2014) showed that using the SLOOS itself as supply shocks overstates the effect of supply shocks on the real economy.

[7]Other studies, including those by Ciccarelli et al. (2015) and Cappiello et al. (2010), use aggregated survey data to identify bank loan supply shocks in the United States and Europe, focusing on the study of the credit channel of monetary policy shocks instead of the role of bank loan supply shocks.

studies have examined the Japanese bank loan market in the 2000s even though the growth rates of aggregate bank loans and economy remained quite low in the early 2000s. Amiti and Weinstein (2013) are an exception in terms of their dataset coverage; using a bank-firm matched loan data over three decades, they showed that idiosyncratic bank shocks can explain 40% of aggregate loans and thus these shocks affect firm investment. This paper, using the Tankan dataset over three decades, provides us with a deeper understanding of the loan supply shock effect on the real economy in a developed country.

The rest of the chapter is organized as follows. Section 3.1 provides a detailed description of the Tankan survey and the identification methodology. Section 3.2 reports the estimation results in the full sample period. Section 3.3 examines the loan supply shock effects during the past two decades and performs a counterfactual analysis for the two financial crises. Finally, Section 3.4 gives concluding remarks. Appendix C describes our variance decomposition methodology.

3.1 Data and Methodology: Tankan Approach

This section describes the Tankan survey data and our estimation strategy. Subsection 3.1.1 provides the detailed description of the Tankan survey, which I used for identify a bank lending stance shock. Subsection 3.1.2 explains how to identify the effects of loan supply shocks using a VAR system of macroeconomic variables.

3.1.1 Tankan Survey and Bank Lending Stance Shocks

To identify bank loan supply shocks, I use the Tankan Survey data collected by the Bank of Japan. This quarterly survey asks over 11,000 firms regarding their current and future business conditions.[8] Sampled firms in the survey are chosen on the basis of the Establishment and Enterprise Census conducted by the Internal Affairs and Communications. The Tankan survey has 31 industry and 3 firm size categories. One question asks firms regarding the lending attitude of financial

[8] Motonishi and Yoshikawa (1999) have more detailed discussion of the Tankan survey.

institutions with firms having to choose between "tight," "easy," or "normal." This allows us to construct a diffusion index (D.I.) by aggregating all firms in an industry i as follows:

$$Stance\ D.I._{it} = (N_{it}^{E} - N_{it}^{T})/N_{it} \times 100 \tag{3.1}$$

where N_{it}^{E} and N_{it}^{T} denote the number of firms who answered "easy" and "tight," respectively. N_{it} denotes the number of firms in industry i in the Tankan survey.

The Stance D.I. is constructed to capture supply side factors in bank loan markets, which I exploit to estimate the effects of bank loan supply shocks. Following Bassett et al. (2014), I assume that a quarterly change of the Stance D.I. follows the AR(1) process as follows:

$$\Delta Stance\ D.I._{it} = \delta_i + \beta_i \Delta Stance\ D.I._{it-1} + e_{it} \tag{3.2}$$

where δ_i and e_{it} denote a industry i fixed effect and an error term, respectively.

However, as discussed in the introduction, the Stance D.I. would be affected more or less by other factors than loan supply shocks. For example, firms that experienced a decrease in demand for their goods are likely to face a severe stance from banks because banks expect the shrink of the firms' business. Accordingly, the Stance D.I. may reflect demand shocks for their good, instead of bank loan supply shocks if such firms answered the question with "tight."

To overcome the estimation bias caused by using the raw Stance D.I. data as loan supply shocks, this study adjusted for other factors that affected the Stance D.I. by following the methodology of Bassett et al. (2014). In the Tankan survey, each firm's panel data is not publicly available. Therefore, I do not adjust for each firm's characteristics as Bassett et al. (2014) did for banks. Rather, I use industry-level data and control for other factors such as loan demand shocks in each industry. Given that loan demand shocks vary across industries, this methodology enables us to obtain a cleaner loan supply shock indicator than using data aggregated at the whole economy level.

In the baseline model, I included the Demand D.I. for goods and service in each industry to adjust for loan demand factors in its Stance D.I. In the Tankan survey, firms are also asked regarding current demands of services and goods in their industry, which firms answer with "increased," "decreased," or "unchanged." More specifically, the demand D.I. is constructed as follows,

$$Demand\ D.I._{it} = (N_{it}^{I} - N_{it}^{D})/N_{it} \times 100, \tag{3.3}$$

where N_{it}^{I} and N_{it}^{D} denote the number of firms that answered "increased" and "decreased," respectively. Using this demand D.I., we disentangle bank loan supply shocks from firm-side factors in the Stance D.I. as follows,

$$\begin{aligned}\Delta Stance\ D.I._{it} =& \delta_i + \beta_i \Delta Stance\ D.I._{it-1} \\ &+ \gamma_{1i}\Delta Demand\ D.I._{it} + \gamma_{2i}\Delta Demand\ D.I._{it-1} + u_{it}.\end{aligned} \tag{3.4}$$

The demand D.I. for goods and service serves as a proxy for firm-side factors that affect the Stance D.I.; in other words, by regressing the Stance D.I. on the Demand D.I., we obtain the residual u_{it} that is orthogonal to firm-side factors represented by the Demand D.I. Here, lower demand for goods and service in each industry is associated with the low performance of firms in that industry, leading to a tight lending stance of their banks.

Moreover, other factors such as banks' perspective for the economic development are supposed to affect the Stance D.I. Therefore, I include the other control variables X_{it-1} in an alternative model as follows:

$$\begin{aligned}\Delta Stance\ D.I._{it} =& \delta_i + \beta_i \Delta Stance\ D.I._{it-1} \\ &+ \gamma_{1i}\Delta Demand\ D.I._{it} + \gamma_{2i}\Delta Demand\ D.I._{it-1} + \eta_i X_{it-1} + u_{it}.\end{aligned} \tag{3.5}$$

More specifically, a one-period lagged value of Nikkei 225 and bank stock index return, the change in the business condition D.I. and GDP growth rates are included as other control variables in the alternative model. As discussed in Bassett et al. (2014), these control variables and the Demand D.I. might be correlated with loan supply shocks to some extent. If the correlation is positive, which is a plausible assumption, we would underestimate the loan supply shock effects. Therefore, we conducted estimations using the raw Stance D.I., in addition to adjusted lending stance shocks in order to understand how our adjustment affect the estimation results.

Finally, bank lending stance shocks for each industry i can be aggregated by weighting u_{it} with a weight w_i as follows:

$$s_t = \sum_{i=1}^{I} u_{it} w_i \tag{3.6}$$

where I indicates the number of industries. The estimation of u_{it} is simply conducted by running an OLS regression for each industry and by allowing the coefficients on the explanatory variables to vary across industries in equation (5). The weight, w_i, is calculated as a ratio of the number of firms in each industry to the total number of firms from the Tankan Survey.

3.1.2 Identification of Bank Loan Supply Shock Effects

To estimate the effect of bank loan supply shocks on the real economy, I follow the methodology of Stock and Watson (2013) by using a VAR model with the aggregate lending stance shocks obtained in the previous subsection as our instruments. The strategy focuses on the partial identification of fundamental shocks. More specifically, I assume that bank loan variables and macroeconomic variables are approximated by a VAR system with p number of lags. Namely, the variables are represented as follows:

$$Y_t = \sum_{p=1}^{P} \beta_p Y_{t-p} + \nu_t, \tag{3.7}$$

where ν_t denotes reduced form shocks of the VAR system. We assume that ν_t is represented by a linear combination of some fundamental shocks, μ_t: In other words. we assume that $\nu_t = B\mu_t$ holds with $n \times n$ matrix B. Moreover, I define Σ_μ as a variance-covariance matrix of the fundamental shocks μ_t. Thereafter, I assume that s_t is a valid and relevant instrument for a bank loan supply shock, which is defined as the first element of vector μ_t without loss of generality. More precisely, I assume that the following conditions hold:

$$E(s_t\mu_{1t}) = \alpha, \tag{3.8}$$

$$E(s_t\mu_{jt}) = 0 \ for \ j \neq 1, \tag{3.9}$$

and

$$E(\mu_t\mu_t') = \Sigma_\mu = D \tag{3.10}$$

where D is a $n \times n$ diagonal matrix and μ_{1t}, the first element of vector μ_t, is a bank loan supply shock. Thereafter, using the instrument s_t, we can identify the fundamental bank loan supply shocks up to a scale and sign as follows,

$$E(s_t\nu_t) = E(s_tB\mu_t) = B_1\alpha \tag{3.11}$$

where B_1 is the first column vector $(n \times 1)$ of B. Defining $b \equiv B_1\alpha$, we can take the sample mean of $\hat{s}_t\hat{\nu}_t$ to estimate b as follows,

$$\hat{b} = \sum_{t=1}^{T} \frac{1}{T}\hat{s}_t\hat{\nu}_t. \tag{3.12}$$

Using the identified vector b, we can calculate the impulse response functions (IRFs), IRF_h, to a negative bank loan supply shock in time horizon h as follows,

$$IRF_h = -\psi_h b/\sigma_s \tag{3.13}$$

where ψ_h denotes the impulse response functions to non-orthogonalized shocks for horizon h in a reduced form VAR and σ_s is a standard deviation of s_t. In Equation (3.13), for normalization, I calculate the IRFs to a bank loan supply shock associated with a one standard deviation negative bank lending stance shock. This point will be clear if we rewrite Equation (3.13) by assuming $E(s_t) = 0$ as follows,

$$\begin{aligned} IRF_h &= -\psi_h \frac{B_1 \alpha}{\sigma_s} = -\psi_h \frac{B_1 \alpha}{E({s_t}^2)} \sigma_s \\ &= -\psi_h \frac{B_1 E(s_t \mu_{1t})}{E(s_t^2)} \sigma_s \\ &= -\psi_h B_1 a \sigma_s \end{aligned}$$

where a denotes the coefficient of s_t in a linear projection of μ_{1t} on s_t. In this manner, we can identify the effects of bank loan supply shocks. To conduct a variance decomposition, we have some limitation in understanding a contribution of a fundamental supply shock since we do not estimate μ_{1t} itself. Appendix C discusses this issue in a more detail. The next section presents the estimation results using the Japanese Tankan data.

3.2 Estimation Results

The estimation methodology takes three steps. First, I estimate the aggregate lending stance shocks. Second, I estimate the reduced form VAR system. Finally, we can estimate the real effects of the bank loan supply shocks using the bank lending stance shocks as an instrument.

3.2.1 Aggregate Bank Lending Stance Shocks

To estimate the aggregate bank stance shocks, I use firms of of all firm size and industries for 28 years from 1986 through 2013.

Adjusted aggregate bank stance shocks are plotted in Figure 3.1 with the weighted average of the bank Stance D.I. and Demand D.I. When several Japanese banks went bankrupt in the late 1990s, the stance shocks plunged. This time frame corresponds to that identified in the previous literature as experiencing a credit crunch (Woo 2003). Compared to the late 1990s, bank lending stance shocks declined less during the 2008 financial crisis, an occurrence that coincides with the prevailing view that the Japanese financial system remained relatively healthy.[9] However, the Japanese GDP declined deeply after the 2008 financial crisis, reflecting weak global demand. Figure 3.1 indicates that the demand D.I. decreased more deeply after the 2008 crisis than during the late 1990s. This figure implies that we successfully captured the different features of these two periods with the Demand D.I. and Stance D.I.

In this study, I estimate bank loan supply shocks as exogenous shocks. Regulation changes can be considered as one of the main original sources of loan supply shocks.[10]

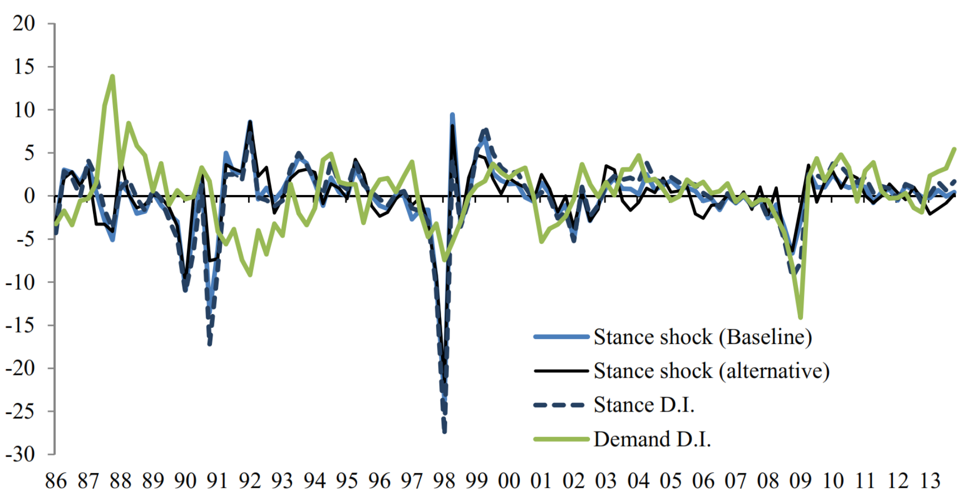


Figure 3.1: Bank lending Stance D.I., Demand D.I. and stance shocks

Notes: The alternative model includes a one-period lagged value of Nikkei 225 and bank stock index return, the change in business condition D.I. and GDP growth rates as control variables in addition to changes in goods and service demand D.I..

[9]For example, The Bank of Japan (2009) and Uchino (2013) argued that Japanese banks remained relatively financially sound during the 2008 financial crisis.

[10]See Section 3.3 for a detailed discussion of Japanese regulation changes in the 1990s and the 2000s.

3.2.2 Estimation of the Reduced Form VAR

As a second step to estimate the real effect of the bank loan supply shocks, I estimate the VAR system with six macroeconomic variables including the real GDP, CPI, bank current accounts held in the Bank of Japan, monetary policy target interest rates,[11] and two bank loan variables.

These bank loan variables include the outstanding amount of total bank loans and those made for investment purposes offered by Japanese domestic banks. These data are collected from the "Assets and Liabilities of Domestically Licensed Banks" and the "Loans and Bills Discounted by Sector" survey, which are conducted by the Bank of Japan. I used the first difference of the logarithm of the outstanding amounts of the bank loans after a seasonal adjustment. Following Bassett et al. (2014), I include the total bank loan variable that covers a broad range of loans such as consumer loans, to capture the role of the bank loans as much as possible. Considering that the Stance D.I. in the Tankan survey is supposed to mainly reflect shocks to firms, I also include the bank loan variable for investment into our VAR system.

As a monetary policy variable, I use the growth rates of the outstanding amount of banks' current account held in Bank of Japan. After Japan's overnight call rate hit the zero lower bound in March 2001, the Bank of Japan implemented a quantitative easing policy where a certain level of the current account is set as a policy target. Although the Bank of Japan terminated the quantitative monetary policy in 2006, the 2008 financial crisis forced it to employ comprehensive monetary easing policy in 2010. The policy was not directly aimed at a certain level of bank current accounts. However, it is a useful variable to indicate the Bank of Japan's monetary policy stance. Hence, I use the first log-difference of the outstanding amount of current accounts as a monetary policy variable. For GDP and CPI, we use the log difference of the seasonally adjusted series. In addition to the six macroeconomic variables, I include two variables to control for consumption tax introduction and hike in April 1989 and April 1997, respectively. Following Bayomi

[11]Before 1997, the discount window rate was used as a target rate by the Bank of Japan, while the overnight call rate has been used subsequently. Therefore, one variable was constructed by connecting overnight call rates and discount window rates.

(2001), I define each variable so that it sums to zero over time and thereby the tax effect cancels out before and after the tax change;[12] in other words, these dummy variables are expected to absorb the tax effects on the macroeconomic variables before and after the tax introduction and hike. In total, I include the six macroeconomic variables, two tax variables and a constant term in the VAR system.

The data and patterns of the six macroeconomic variables after 1986 are illustrated in Figures 3.2, 3.3 and 3.4, where I showed them as year-over-year growth rates except inflation, real GDP and current accounts. Figure 3.2 demonstrates that the growth rates of outstanding bank loans continued to decrease from 1990 until the early 2000s. Figure 3.3 indicates that the growth rates of the real GDP and CPI are very volatile. According to Figure 3.4, the call rates were almost zero after 1999 while the current account increased during the quantitative easing period in the early 2000s.

In the VAR system, the number of lag in the VAR is chosen as one on the basis of the Bayesian Information Criterion (BIC). The next subsection reports the estimation results of IRFs and variance decompositions to examine the effects of bank loan supply shocks on the real economy.

3.2.3 IRFs and Variance Decompositions for Full Sample Period

The bank lending stance shocks $\hat{s}_t$, obtained in the previous step are used to estimate the IRFs to a negative bank loan supply shock, μ_{1t}. Here, a negative shock implies a tightening of banks' lending stance and thereby the deterioration of firms' financing condition.

In this section, to study the extent to which a different specification of bank lending stance shocks affects estimation results, we conduct estimations using raw

[12]For example, the control variable for the introduction of the consumption tax in the second quarter of 1989 takes the value of -1 in the first quarter of 1989, 1 in the second quarter and zero otherwise. The tax hike control variable is defined in the same manner. Furthermore, I conducted a robustness check by defining the variable in another way so that it takes -1 in the second quarter of 1989, 1 in the third quarter of 1989 and zero otherwise. This alternative definition of the control variable does not change the estimation results.

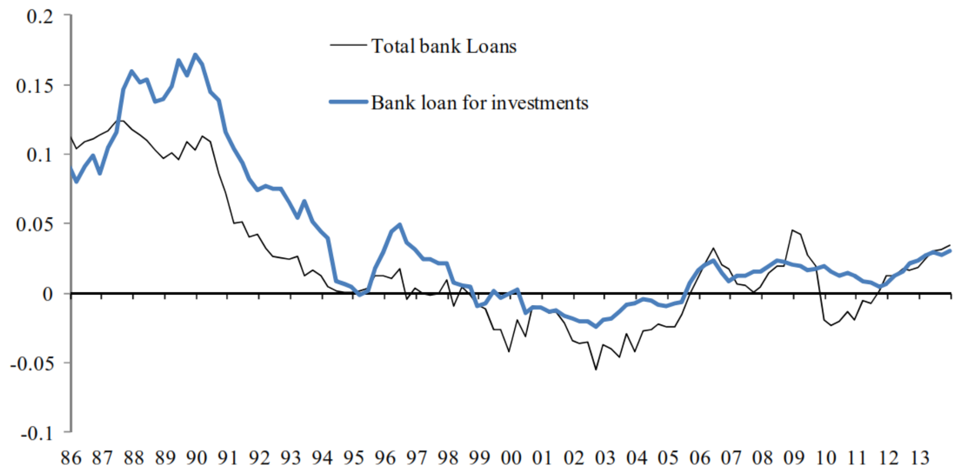


Figure 3.2: Bank Loan Growth Rates

Notes: Year-over-year log growth rates of outstanding bank loan amount. Total bank loans and bank loans for investment are taken from the Assets and Liabilities of Domestically Licensed Banks" and the "Loans and Bills Discounted by Sector" surveys, respectively.

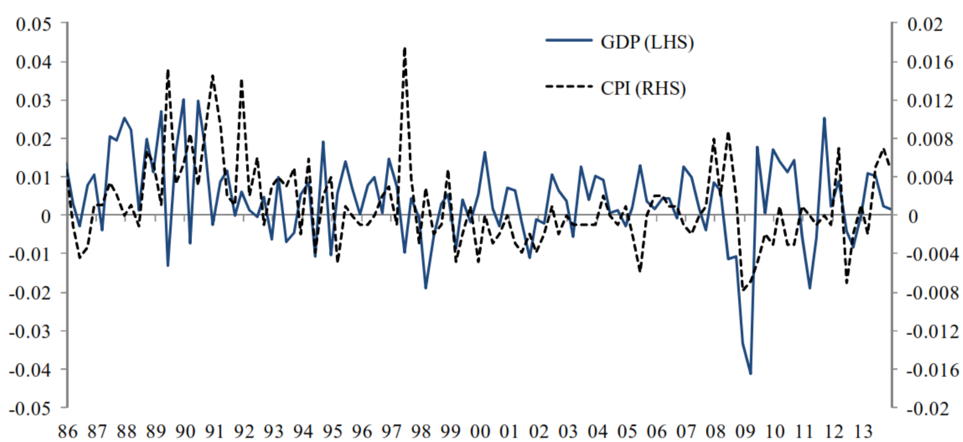


Figure 3.3: GDP Growth Rates and Inflation Rates (CPI)

Notes: Both variables are calculated as the first log difference of the seasonally adjusted quarterly data.

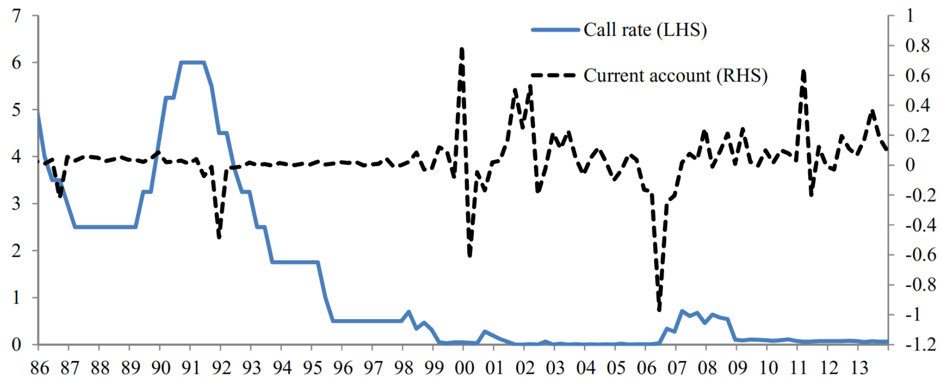


Figure 3.4: Call Rates and Current Account

Notes: The current account is calculated as the log growth rates of banks outstanding current accounts amounts held in the Bank of Japan. Before 1997, call rate indicates the discount window rate.

data of the Stance D.I. and an alternative specification of stance shocks in addition to the baseline model. In the alternative specification, I include the lagged value of GDP growth rates and stock returns as the control variables ($X_{i,t-1}$) in equation (5). The stock return is calculated as the first log difference of the Nikkei 225 index.

Figure 3.5 illustrates the cumulative change in the variables in response to a negative bank loan supply shock, obtained from two different specifications of bank stance shocks and the raw Stance D.I. Note that the baseline model includes only the Demand D.I. as a control variable in equation (5) to identify bank lending stance shocks. In Figure 3.5, the shaded band indicates the 90% confidence intervals based on a bootstrap of 3,000 iterations for the baseline specification.

In the baseline model, both of bank loan variables—bank loans for investment and total bank loans—gradually decreased significantly to around -0.8% and -0.5%, respectively, in the 20th quarter. This result indicates the bank lending stance shocks reflect the changes of banks' lending behavior that caused the actual decrease in bank lending.

As bank loans decrease, GDP also shrinks significantly, declining to -0.4% in the 20th quarter. Given the low level of growth rates of Japanese economy in these three decades, this result implies that loan supply shocks had some important role in its downturn.

Regarding CPI, the simultaneous response is inflationary even though the magnitude of 0.05% is small. One possible interpretation of the CPI's positive response to a negative loan supply shock is that reduced bank loans depressed the supply side of output, causing an inflationary pressure. In the 20th quarter, the median estimates indicate a persistent but small decline of about −0.07%. This small and insignificant effect suggests that negative bank supply shocks were not the main driving factors of deflation in Japan. The current account simultaneously increases, responding to the loan supply shock. Thereafter, it gradually increases to approximately 2% at the end of our forecast horizon although this increase is insignificant. This finding indicates that the Bank of Japan reacted aggressively to bank loan supply shocks to mitigate the negative effect on the real economy by easing the monetary policy. The IRFs for the call rate also indicates that the Bank of Japan eased its monetary policy by responding to a bank loan supply shock, although the first response to the shock is positive. IRFs obtained by using the raw stance D.I. and the alternative specification of lending stance shocks show a small difference from those based on the baseline model.

To investigate the contribution of loan supply shocks to fluctuations in real economy, I report estimation results for variance decompositions in Figure 3.6. Figure 3.6 indicates that bank loan supply shocks explain about 4% and 6% of bank loans for investment and GDP fluctuations, respectively. For other four variables, the contribution of loan supply shocks is less than 5%. Considering the results of IRFs, we can infer that bank loan supply shocks were not main driving factors of macroeconomic fluctuations over these three decades on average, although they significantly affected the real economy in some periods.[13]

In our alternative specification, the variance decompositions also show a low

[13] Compared to the variance decompositions in United States implemented by Bassett et al. (2014), the contribution found in this study does not increase over forecast horizons and is relatively small. In other words, in this VAR model and estimation, bank loan supply shocks were not greatly transmitted over the second quarter of the forecast horizon. There may be several possible explanations why bank loan supply shocks have low contributions after the second period. For example, by omitting an important variable, we might miss some important amplification mechanism of bank loan supply shocks in the economy.

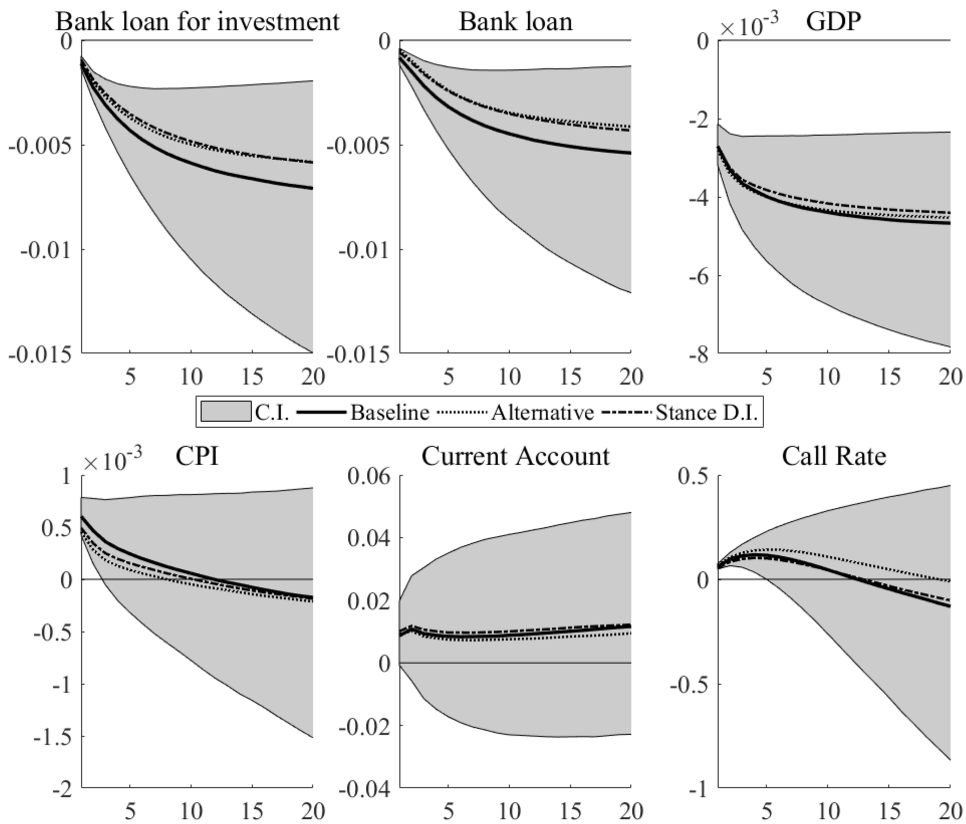


Figure 3.5: IRFs to a Negative Loan Supply Shock for the Full Sample

Notes: Figure 3.5 shows the impulse response functions (shown as a cumulative change) to a bank loan supply shock that is associated with a bank lending stance shock of one standard deviation calculated from the baseline specification. The shaded bands represent the 90% level confidence interval from the baseline model based on 3000 bootstrap replications. Alternative denotes the median estimates from the alternative specification of bank stance shocks wherein we adjusted for the lagged value of GDP growth rates and stock index returns. Stance D.I. denotes the median estimates from the other specification wherein we used the weighted average of the raw Stance D.I. as lending stance shocks. Alternative is represented by a dotted line. Similarly, Stance D.I. is represented by another dotted line.

contribution of about 6% to GDP fluctuations. Furthermore, even using the raw Stance D.I., about 8% of GDP fluctuations is attributable to loan supply shocks, although it is larger than that from our baseline model as expected. These results indicate that bank loan supply shocks were not main driving forces of the real economy, although they affected significantly bank loans and GDP.

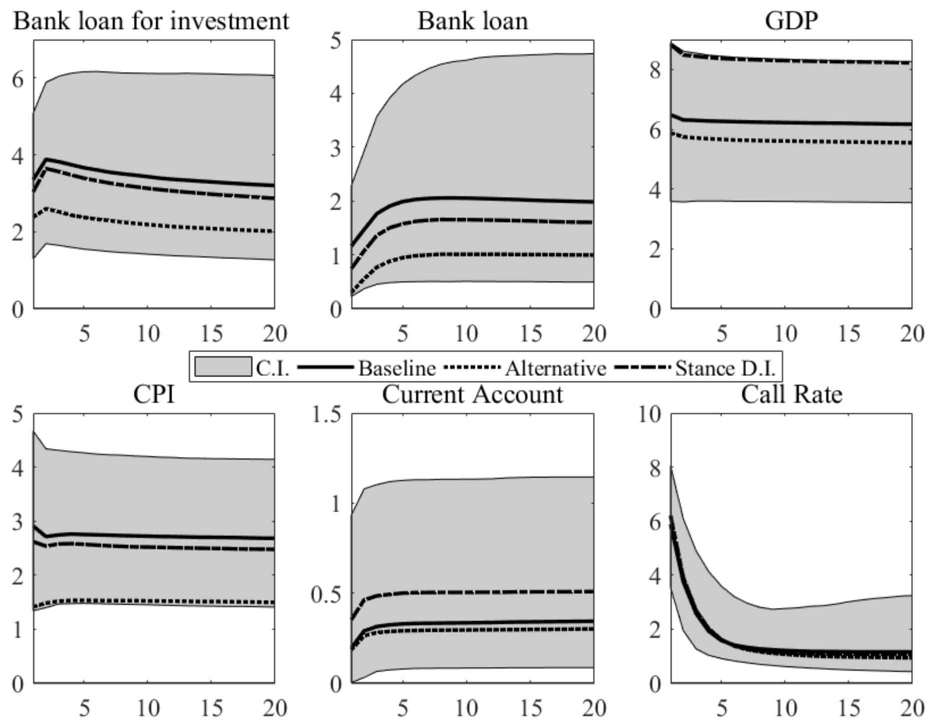


Figure 3.6: Variance Decomposition for the Full Sample

Notes: Figure 3.6 shows the contribution of a loan supply shock to the forecast error variance of each variable. The shaded bands represent the 90% level confidence interval from the baseline specification of lending stance shocks based on 3000 bootstrap replications. Alternative denotes the median estimates from the alternative specification wherein we adjusted for the lagged value of GDP growth rates and stock index returns. Stance D.I. represents the median estimates from the other specification wherein we used the weighted average of the raw Stance D.I. data as lending stance shocks.

3.3 Loan Supply Shocks in the Recent 20 Years

In this section, I focus on the development of bank loan supply shocks in the past 20 years. After the burst of the Japanese bubble economy, in the 1990s, Japanese banks suffered due to continuing declines in asset prices, which increased nonperforming loans and lowered their capital adequacy ratios.

The government took several steps to resolve the problem, including bailing out some failed mortgage banks in 1995. Moreover, in 1998, the government injected capital into 13 large banks. Nonetheless, some large banks such as the Long Term Credit Bank of Japan went bankrupt in 1998. Since even after the first capital injection, some banks still had insufficient capital ratios to cover losses made by accumulated nonperforming loans, the Japanese authority implemented a second and third capital injection in 1999 and 2002.[14] In fact, we can observe that banks' lending stance was tightened during these turmoil periods as illustrated in Figure 3.1.

In addition to the deterioration of banks' financial condition, in the late 1990s and early 2000s, the regulation over Japanese banks also changed drastically. At the end of the 1997 fiscal year, the Ministry of Finance forced Japanese banks to conduct self assessments of their loans, and to more rigorously and transparently write-off loan losses.[15] Simultaneously, the prudential policy guideline for the prompt corrective pact was introduced, allowing the regulator to intervene in poorly capitalized banks, on the basis of the capital adequacy ratio calculated following international regulations, known as the risk-based capital standard. These regulatory changes forced banks to recognize the lack of their capital and affected their lending behavior. Indeed, using a late 1990s dataset, some previous works found evidence that a capital crunch happened in Japan.[16]

In 2002, the Financial Revitalization Plan was introduced to prompt the disposal of nonperforming loans. Consequently, nonperforming loan disposals were

[14]For a detailed discussion of the effects of the Japanese public capital injection, see Gianetti and Simonov (2013).

[15]See Watanabe (2007) for detailed discussion of the regulations in the late 1990s and early 2000s.

[16]See e.g., Woo (2003) and Gan (2007a).

accelerated and their amounts decreased after 2003. This period coincides with the trough in the bank loan growth rates as shown in Figure 3.2. This fact suggests that the regulation changes affected banks' behavior through the rigorous treatment of their lending.

This section reports the estimation results obtained using the dataset covering only the period post 1995 to investigate the effect of the deterioration of bank health and the regulation changes in the late 1990s and early 2000s on the performance of the Japanese economy.

Furthermore, these two decades in Japan are characterized by an unprecedentedly low interest rate environment. In particular, the Bank of Japan effectively lowered the policy rate to zero in the late 1990s and has maintained a low rate for two decades except for some short periods during which it increased rates by some basis points (See Figure 3.4 for the historical path of its policy rates). In this section, I also report the estimation results obtained using only subsample periods when the zero lower bound was binding to examine the real effect of bank loan supply shocks in a zero lower bound environment.

Subsection 3.3.1 reports the estimation results of IRFs and variance decompositions for the past 20 years. Subsection 3.3.2 performs a counterfactual analysis during the two financial crises in the late 1990s and 2008 to indicate the importance of bank loan supply shocks. Subsection 3.3.3 compares the estimation results with and without a zero lower bound constraint.

3.3.1 Estimation Results: the Past 20 Years

In the VAR system for the post 1995 subsample, I only include the current account as a monetary policy variable because the overnight call rate showed a small variation in this period. In this subsection, I only show the estimation result for the baseline specification of bank stance shocks.

Figures 3.7 illustrates the estimated IRFs for the subsample period with the median estimates from the full sample estimation obtained in the previous section, in order to make a comparison between them.[17] The shaded bands indicate the 90%

[17]IRFs in Figure 3.7 are normalized as a response to a negative lending stance shock of one

confidence intervals for subsample estimations. In Figure 3.7, we can observe that bank loan supply shocks have significant effects on bank loans and GDP, which are qualitatively same as what we found in the full sample estimation. However, the response of bank loans for investment is smaller than in the full sample estimation. On the other hand, GDP responds to a bank loan supply shock in a similar manner as in the full sample estimation. This difference implies that in the past 20 years, a smaller decline in bank loans is associated with a larger decline in real GDP.

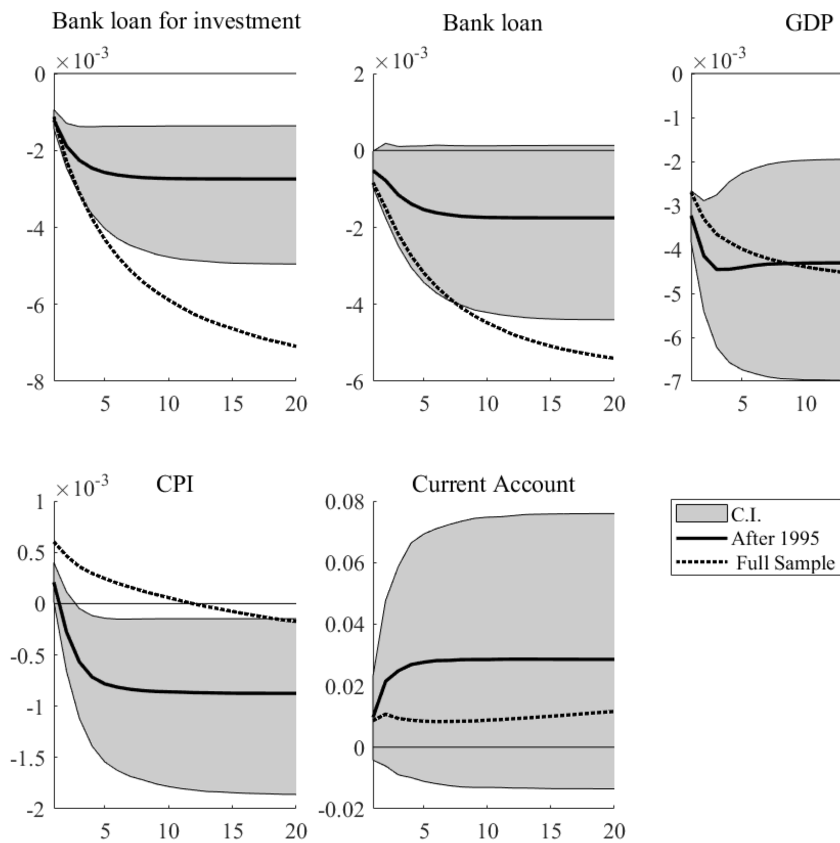


Figure 3.7: IRFs to a Negative Loan Supply Shock for 1995–2013

Notes: Figure 3.7 shows the impulse response functions to a bank loan supply shock that is associated with a bank lending stance shock of one standard deviation calculated from the full sample. The shaded bands represent the 90% level confidence intervals from the subsample of 19952013 based on 3000 bootstrap replications. Full sample represents the median estimates from the full sample estimation.

standard deviation calculated in the full sample period.

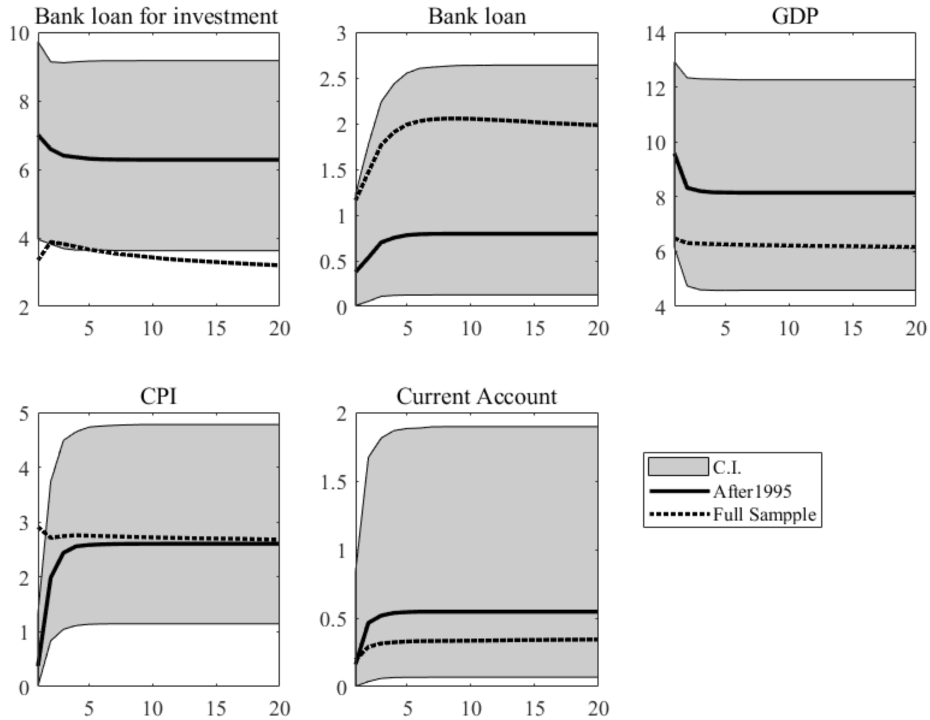


Figure 3.8: Varinace Decomposition for 1995–2013

Notes: The figure shows the contribution of a loan supply shock to the forecast error variance of each variable. The shaded bands represent the 90% level confidence intervals from the subsample of 1995-2013, based on 3000 bootstrap replications. Full sample represents the median estimates from the full sample estimation.

CPI also decreased gradually to -0.1% significantly. This result shows that bank loan supply shocks had a deflationary pressure on the economy in the recent 20 years. The current account increased by more than 2% although it is insignificant at the 10% level. This implies that the Bank of Japan aggressively responded to bank loan supply shocks by providing banks with liquidity to mitigate the economic contractions and the deflationary effect.

The variance decompositions in Figure 3.8 indicate that approximately 8% of GDP fluctuations are explained by bank loan supply shocks in this subsample period, which is larger than in the full sample estimation. This result suggests that the past two decades were time in which bank supply shocks played a relatively important role. On the other hand, the fluctuation of CPI is explained less than 5% by loan supply shocks. Overall, loan supply shocks contributed to less than 5% of macro economic fluctuations except for bank loan for investment and GDP, which suggests that bank loan supply shocks were not the main determinant for the fluctuations in the real economy, even after 1995.

3.3.2 Two Financial Crises: the late 1990s and 2008

In the previous subsection, I showed that bank loan supply shocks contributed to only approximately 8% of the fluctuations in Japan's real GDP in the past 20 years on average. However, this does not necessarily mean that bank loan shocks were always unimportant for real economy. To show loan supply shocks might play an important role in some periods, this subsection investigates the role of bank loan supply shocks in two periods: the late 1990s and the 2008 financial crises, conducting a counterfactual analysis.

Using the estimation results in the previous subsection, we conduct a counterfactual analysis to reveal the dynamics of the real economic variables without bank loan supply shocks. More concretely, in this analysis I assume that after the third quarter of 1997 (or the first quarter of 2008), the Japanese economy had not been exposed to bank loan supply shocks, keeping other shocks as they were. Thereafter, we can compare a cumulative change to actual one for each variable.

Figure 3.9 (top) shows the cumulative GDP changes starting in the third quarter of 1997. This figure indicates that in 1998, bank loan supply shocks were the determinant of declining GDP. Without loan supply shocks, GDP would have remained positive in 1998, and in 1999, the decline in GDP could have been half of realized values. This result indicates that bank loan supply shocks have played an important role in both absolute and relative term.

To evaluate the impact of loan supply shocks in the late 1990s, in Figure 3.9 (bottom), I report the result of a counterfactual analysis assuming that there had been no loan supply shocks after the first quarter of 2008. In Figure 3.9, the counterfactual change for 2008 indicates that the difference between the realized and conterfactual cases was approximately 2% points. Although the difference between realized and counterfactual is large during the 2008 crisis, the decline of realized GDP is approximately -8% at the bottom. This implies that the relative importance of bank loan supply shocks was not as large as in 1998.

Figures 3.10 shows cumulative changes in CPI during the 1998 and 2008 crises at the top and the bottom, respectively. We can observe that the deflationary effect caused by bank loan supply shocks was not substantial. In other words, even without bank loan supply shocks, Japanese inflation rates would remain low.

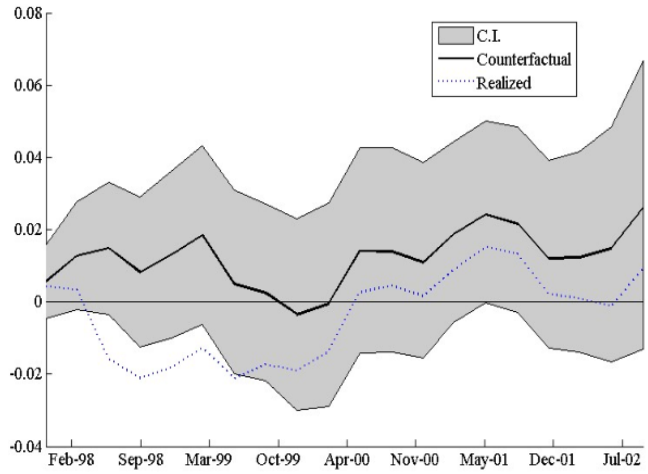
The result in the counterfactual analysis supports the prevailing view that the banking system did not deteriorate in the 2008 crisis as much as in the late 1990s: in the late 1990s crisis, without the bank loan supply shocks, Japanese GDP would have remained positive in 1998 and its 1999 decline would have been half of the realized values. Furthermore, the result shows that bank loan supply shocks were not the main factor to lower inflation after the crises.

3.3.3 Loan Supply Shocks with a Zero Lower Bound Constraint

When interest rates reach a zero lower bound, a negative bank loan supply shock is expected to substantially affect the real economy because the available monetary policy tools for the central bank to mitigate such shocks are limited. This mechanism is well known in theoretical literature, but there are few empirical studies. In this subsection, IRFs are estimated using a subsample during which overnight call rates essentially reached the zero bound. More concretely, the subsample includes three periods: 1999:Q1–2000:Q2, 2001:Q1–2006:Q2, and 2008:Q4–2013:Q4. Figure 3.11 shows the estimated IRFs when the monetary policy is under a zero lower bound constraint, including the current account as a monetary policy tool. To see the difference more clearly, Figure 3.11 also shows median estimates of IRFs that were obtained by using the full sample as already shown in Figure 3.5.

Figure 3.11 shows that bank loan supply shocks induced a deflationary pressure in a zero lower bound environment; CPI declined significantly by 0.05% in response to a negative loan supply shock. This result indicates that the loan

The Late 1990s



The Late 2000s

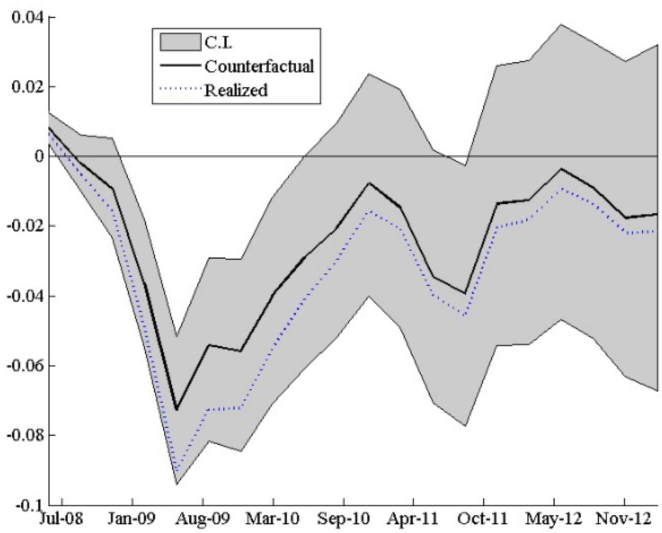
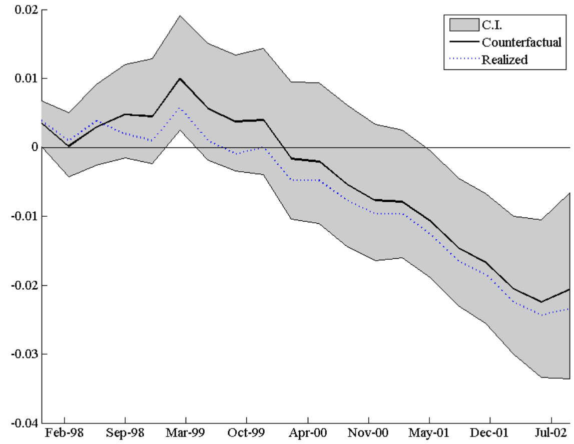


Figure 3.9: Cumulative Change in GDP

Notes: Solid line (counterfactual) represents the median estimates of cumulative changes in GDP growth rates since the third quarter of 1997 (top) and the first quarter of 2008 (bottom). The counterfactual analysis was performed by assuming that no bank loan stance shocks occurred after the third quarter of 1997 (or the first quarter of 2008) on the basis of the estimation result obtained in Subsection 3.3.1. The shaded bands indicate the 90% level confidence interval based on 3000 bootstrap replications. The dotted line (realized) indicates the actual path of GDP cumulative changes.

The Late 1990s



The Late 2000s

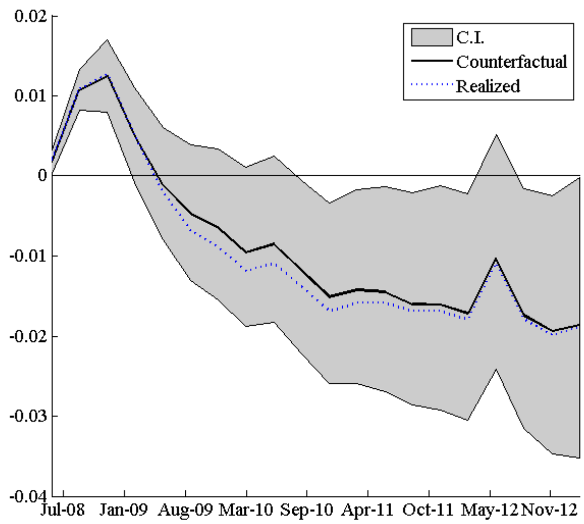


Figure 3.10: Cumulative Change in CPI

Notes: Solid line (counterfactual) represents the median estimates of cumulative changes in GDP growth rates since the thrid quarter of 1997 (top) and the first quarter of 2008 (bottom). The counterfactual analysis was performed by assuming that no bank loan stance shocks occurred after the fourth quarter of 1997 (or the first quarter of 2008) on the basis of the estimation result obtained in Subsection 3.3.1. The shaded bands indicate the 90% level confidence interval based on 3000 bootstrap replications. The dotted line (realized) indicates the actual path of GDP cumulative changes.

supply shocks had a significant effect on CPI whereas in a normal environment, CPI did not decrease significantly by responding to the shock. The current account increased significantly by approximately 5%. These two results imply that the decline in CPI when a zero lower bound constraint was binding was substantial especially for the first five quarters, although it was mitigated by the central bank's aggressive monetary policy easing.

Figure 3.12 shows the variance decomposition with zero lower bound constraints. This figure shows the high contribution of bank loan supply shocks to the macroeconomic variables in the subsample period with zero lower bound constraints, especially to GDP. For GDP, the shocks are attributable to approximately 15% at a maximum of its fluctuations with a zero lower bound, whereas in a non-zero lower bound environment the shocks contribute to about 6% as shown in Figure 3.12.

The estimation results with a zero lower bound constraint shows that bank loan supply shocks substantially decreased GDP, and CPI, despite the central bank's efforts to mitigate their effects on the real economy.

3.4 Conclusion

In this study, I estimated the effect of bank loan supply shocks using bank lending stance shocks derived from the Tankan survey data in Japan. The identified lending stance shocks enable us to investigate the effect of bank loan supply shocks on the real economy over about 30 years in a consistent manner. This methodology has some advantages compared to that used in previous studies, which mainly relied on bank balance sheet data.

Using bank lending stance shocks, I obtain three substantial conclusions regarding the effects of loan supply shocks. First, I find that a negative bank loan supply shock significantly decreases GDP: a negative supply shock associated with one standard deviation of the stance shock decreased GDP by about 0.5%. However, the contribution of the shock to GDP fluctuations is less than 10% in the variance decomposition. This low contribution suggests that bank loan supply

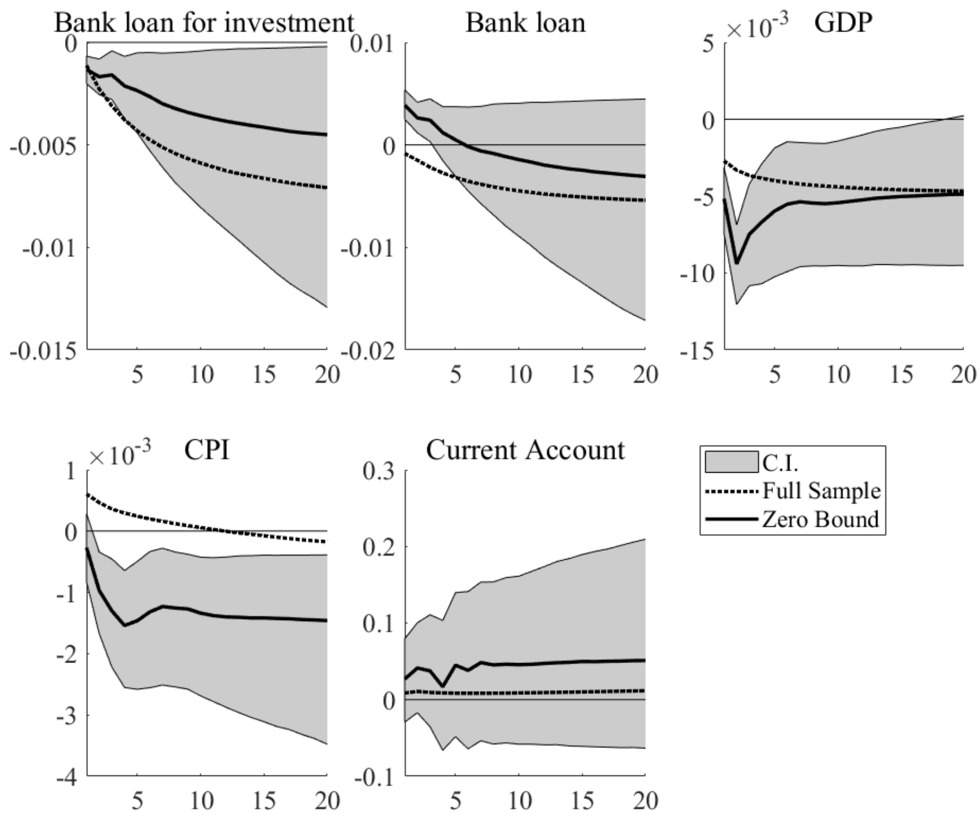


Figure 3.11: IRFs in a Zero Lower Bound Environment

Notes: The figure shows the impulse response functions to a bank loan supply shock that is associated with a bank lending stance shock of one standard deviation calculated from the full sample periods when the policy rates were on a zero lower bound. The shaded bands represent the 90% level confidence intervals from the subsample when a zero lower bound is binding, based on 3000 bootstrap replications. The dotted line indicates the median estimates from the full sample.

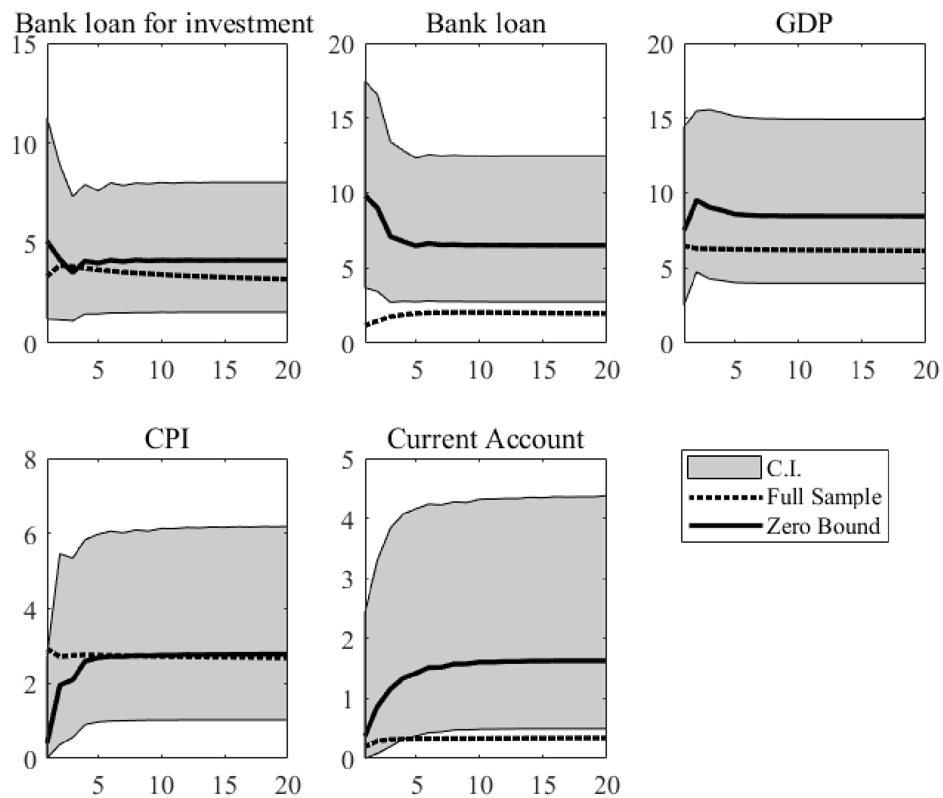


Figure 3.12: Variance Decompositions in a Zero Lower Bound Environment

Notes: The figure shows the contribution of a loan supply shock to the forecast error variance of each variable when the policy rates were on a zero lower bound. The shaded bands represent the 90% level confidence intervals from the baseline model, based on 3000 bootstrap replications. The dotted line indicates the median estimates from the full sample.

shocks were not main factors of the fluctuations of Japan's real economy on average.

Second, I showed that after 1995, a negative supply shock played a more important role than in the previous decade: The variance decomposition revealed that bank loan supply shocks contributed approximately 8% to GDP in the past 20 years. Moreover, I find that the Bank of Japan strongly responded to a negative supply shock by easing the monetary policy, although CPI was not significantly affected by negative loan supply shocks. Furthermore, the counterfactual analysis showed that the supply shocks suppressed GDP growth rates significantly in the late 1990s financial crisis: GDP growth rates would have remained positive in 1998 without these shocks, and its decline in 1999 would have been half of the realized outcome. The effects of the shocks in the late 1990s were significant, even if we compared them to those in the 2008 crisis.

Third, the economy in a zero lower bound environment is more vulnerable than under a non-zero lower bound environment: GDP declined by 0.6%, responding to a loan supply shock associated with a stance shock of one standard deviation in a zero lower bound environment. Furthermore, the variance decomposition indicates that the contribution of supply shocks to GDP's fluctuations increased to 10% with a zero lower bound constraint.

This study did not use the firm-level data in Tankan survey, which are not publicly available. Hence, we did not adjusted for firm-specific characteristics. Instead, I utilized industry-level data. This could cause some identification problems in terms of a stance shock because some time-varying unobservable factors might exist in the industry level data, which would be controlled at the firm-level. Moreover, in terms of the dataset, this study used survey data answered by firms instead of banks. This could cause some bias in the estimations of loan supply shock effects because the extracted lending stance shocks might be correlated with loan demand shocks.

Appendix A
Chapter 1

A.1 Construction of Loan-level Matched Sample with M&A, Business Transfer, and Divestiture Activity

As discussed, the Japanese banking sector experienced significant M&A, business transfer, and divestiture activity over the late 1990s and early 2000s. To construct our loan-level dataset, we checked whether succeeding banks took over the merged or eliminated bank's credit claims on its borrowing firms before and after the relevant M&A, business transfer, or divestiture. This Appendix explains how we define the termination of a bank–borrower relationship in the case of M&A, business transfer, and divestiture.

The Case of M&A

Here, we consider the case of an absorption-type merger. If a surviving bank took over a merged bank's loan lent to a borrowing firm after the absorption merger, we assume that the pre-M&A relationship between the merging bank and the borrowing firm continues in the post-M&A relationship between the surviving bank and the firm. That is, the pre-M&A relationship did not terminate at the time of the absorption merger. On the other hand, if no bank took over the loan of the merging bank, we assume that the pre-M&A relationship terminated at the time of the absorption merger.

The Case of Business Transfer

Next, we consider the case in which a bank transferred its business to other banks. In this case, we define a relationship termination as the case of M&A. If we find that the transferee bank took over the loans of the transferor bank, we suppose that the transferor bank also held over pre-transfer relationships between the transferor bank and its borrowing firms, and that the pre-transfer relationships did not terminate. As long as we find that the transferee banks did not take over loans of the transferor bank, we assume that the pre-transfer relationships between the transferor bank and its borrowing firms terminated. We adopt the above way of defining a relationship termination, whether the accepting banks had enjoyed relationships with those borrowing firms before the business transfer or not.

The Case of Merger and Divestiture

We consider the case in which banks merged and then divested. In this case, we should identify which banks formed after the merger and divestiture and whether they took over the loans of the merging banks. If a firm had enjoyed relationships with one of the merging banks before the merger and divestiture, and the firm had a relationship with at least one of the surviving banks after the merger and divestiture, we consider that the relationships between the merging banks and the firm were preserved. That is, the relationships did not terminate. If the firm did not have any relationships with the surviving banks after the merger and divestiture, we consider that the relationships between the merged banks and the firm terminated at that time.

Appendix B

Chapter 2

B.1 Estimation Results for Relation Survival Probability

In Section 2.4, we included the inverse Mills ratio into the bank loan model to control for the survival bias. In this appendix, we show the estimation results of the probit model, which is used to calculate the inverse Mills ratio.

As the literature on relationship banking pointed out, the continuation of a bank-firm relationship depends on both the bank's and the firm's characteristics. As discussed in Section 2.3, our probit regression includes the one-period lags of the firm's leverage ratio (FLEV_{it-1}), return on assets (FROA_{it-1}), interest coverage ratio (FICR_{it-1}), size (FSIZE_{it-1}), the bank's leverage ratio (BLEV_{jt-1}), return on assets (BROA_{jt-1}), size (BSIZE_{jt-1}), bank j's lending exposure to firm i (EXPL_{ijt}), firm i's borrowing exposure from bank j (EXPB_{ijt-1}), and the duration of the relationship between lender i and its borrowing firm j (DURAT_{ijt-1}) as relationship factors. Moreover, we include the number of banks that have lending–borrowing relationships with firm i (NUMBL_{it-1}) and the number of firms that bank j do (NUMBB_{jt-1}). We also include industry dummy variables and conduct the rolling estimation of the probit model year-by-year to incorporate time-varying effects of each variable. This year-by-year estimation means that we do not need to include time dummies.

Table B.1 shows the estimation results and indicates that a higher borrowing and lending exposure and a longer duration of relationships are associated with higher probability of the continuation of relationships. Furthermore, firms with higher profitability tend to continue their relationships with lending banks. A lower firm's interest coverage ratio implies a higher probability of the continuation of the relationship, which suggests that firms with a high dependence on the debt funding tend to continue their relationships with banks. We should also note that a higher bank's leverage was associated with a lower probability of the continuation of relationships until the early 2000s, while a higher bank's leverage is likely to lead to a higher probability of the continuation of relationships from the late 2000s onward. This suggests that in the late 1990s and the early 2000s, the capital crunch happened in terms of the relationship termination, as pointed out by Nakashima and Takahashi (2017). Overall, a higher firm's profitability and dependence on debts finance and higher borrowing and lending exposure are associated with higher probability of the relationship continuation.

Table B.1: Estimation Result for Survival Model of Borrowing-lending Relationships

Fiscal Year	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
BLEV	-0.00442	-0.0299***	-0.0590***	-0.0222*	0.0114	0.0127	0.0100	0.0197*	0.0128	0.0172*	0.0316***
	(-0.52)	(-3.46)	(-6.03)	(-1.69)	(1.19)	(1.25)	(1.02)	(1.96)	(1.39)	(1.82)	(2.77)
BSIZE	-0.0379	0.0481	0.212***	0.0997**	-0.0320	-0.0327	-0.0735*	-0.0371	-0.0468	-0.0381	-0.0560
	(-0.90)	(1.14)	(5.16)	(2.17)	(-0.91)	(-0.79)	(-1.88)	(-1.03)	(-1.30)	(-1.19)	(-1.62)
BROA	0.0600***	-0.00920	-0.128***	-0.0539**	0.0834***	0.0133	-0.101***	-0.0441	-0.0163	0.0370	0.0444**
	(5.03)	(-0.66)	(-4.97)	(-2.54)	(4.47)	(1.15)	(-2.93)	(-0.89)	(-0.52)	(0.93)	(1.98)
FLEV	-0.00533**	-0.00102	0.0145***	0.000600	0.00173	-0.00350	-0.00681***	0.0126***	0.0118***	0.0122***	-0.0142***
	(-2.00)	(-0.40)	(5.97)	(0.24)	(0.66)	(-1.31)	(-2.72)	(5.02)	(4.69)	(5.31)	(-5.85)
FSIZE	0.0369	0.852***	0.106	0.364***	0.108	0.231**	-0.0156	-0.193***	-0.390***	-0.122*	0.153*
	(0.32)	(7.51)	(1.31)	(3.91)	(1.12)	(2.47)	(-0.20)	(-2.94)	(-5.75)	(-1.75)	(1.69)
FROA	0.00525**	0.0154***	0.00908***	0.00101	0.00771***	0.00522***	0.00405**	0.00891***	0.00119	0.0318***	0.00266
	(2.13)	(6.32)	(3.34)	(0.62)	(3.20)	(2.59)	(2.24)	(3.50)	(0.54)	(13.50)	(1.41)
FICR	0.00000957***	0.00000129	0.00000177**	-0.000000292	-0.00000476**	-0.00000275	0.00000221**	-0.00000292**	-0.00000338***	-0.0000254***	-0.00000705***
	(3.72)	(0.41)	(2.34)	(-0.22)	(-2.26)	(-1.42)	(2.12)	(-2.35)	(-3.00)	(-8.30)	(-3.52)
DURAT	0.0104***	0.0116***	0.0127***	0.00977***	0.0126***	0.0130***	0.0173***	0.0207***	0.0168***	0.0215***	0.0235***
	(7.09)	(6.70)	(7.79)	(6.20)	(7.93)	(7.52)	(10.17)	(12.27)	(10.20)	(13.64)	(14.26)
EXPL	0.0233***	0.0328***	0.000290	0.0732***	0.0119*	0.0964***	0.0291***	0.0223***	0.0288***	0.0440***	0.00696
	(4.35)	(3.89)	(0.05)	(6.44)	(1.82)	(6.78)	(3.25)	(3.50)	(3.90)	(5.34)	(1.60)
EXPB	0.0114***	0.0139***	0.0142***	0.00871***	0.0122***	0.0101***	0.00979***	0.0114***	0.00796***	0.00542***	0.00746***
	(11.41)	(11.90)	(12.92)	(8.71)	(12.15)	(9.63)	(9.24)	(10.59)	(8.06)	(5.60)	(7.23)
NUMBL	0.158***	0.267***	0.299***	0.231***	0.260***	0.342***	0.366***	0.183***	0.198***	0.0698**	0.138***
	(5.43)	(8.06)	(9.54)	(7.43)	(7.94)	(9.75)	(10.66)	(5.72)	(6.49)	(2.30)	(4.27)
NUMBB	0.136***	-0.0153	-0.187***	-0.00246	0.0348	0.116***	0.136***	0.0995**	0.132***	0.125***	0.0990***
	(2.98)	(-0.35)	(-4.35)	(-0.05)	(0.95)	(2.75)	(3.40)	(2.47)	(3.25)	(3.50)	(2.66)
N	22808	19230	19359	17770	15713	14823	14859	13902	13854	13677	12371

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. t statistics are shown in parentheses. The dependent variable is the survival dummy variable, which equals one if the borrowing-lending relationship continues in year t, otherwise zero. This table shows the estimation result of the model with industry fixed effects. We also include 5-year moving average values of firm ROA, interest coverage ratio, book leverage ratio, and size to control for time-varying firm fixed effects. The estimated coefficients are not shown in the table.

Table B.1: (continued)

Fiscal Year	2010	2011	2012	2013	2014
BLEV	0.00489	-0.0653***	0.0189	0.0342**	0.0391***
	(0.45)	(-4.48)	(1.29)	(2.56)	(2.66)
BSIZE	-0.0524	-0.0176	0.122***	-0.00673	-0.0280
	(-1.53)	(-0.46)	(3.42)	(-0.24)	(-0.70)
BROA	-0.0105	-1.444***	-0.105	-0.0211	0.00769
(-0.09)	(-9.72)	(-0.92)	(-0.22)	(0.06)	
FLEV	0.00210	-0.0113***	0.0204***	0.0151***	0.00339
	(0.79)	(-3.29)	(5.14)	(4.53)	(0.93)
FSIZE	0.0317	0.493***	0.354***	-0.812***	0.217
	(0.31)	(4.19)	(2.68)	(-6.45)	(1.49)
FROA	0.00413*	-0.0108***	0.00342	0.0173***	0.00634
	(1.78)	(-3.67)	(0.74)	(4.59)	(1.23)
FICR	-0.00000898***	-0.0000111***	-0.00000953***	0.00000210	-0.00000152
	(-3.07)	(-3.42)	(-3.46)	(0.84)	(-0.50)
DURAT	0.0127***	0.0277***	0.0240***	0.00897***	0.0139***
	(8.15)	(13.18)	(11.43)	(6.30)	(8.80)
EXPL	0.0262***	0.0188***	0.0309***	0.0103*	0.00316
	(3.48)	(2.98)	(2.86)	(1.82)	(0.72)
EXPB	0.00870***	0.00663***	0.00586***	0.00360***	0.000273
	(8.28)	(5.66)	(5.16)	(4.02)	(0.29)
NUMBL	0.202***	0.206***	0.0137***	0.0493***	0.0203***
	(5.76)	(5.25)	(3.40)	(13.42)	(5.25)
NUMBB	0.134***	0.184***	-0.000142	0.0000898	0.0000847
	(3.45)	(4.28)	(-1.64)	(1.30)	(0.71)
N	11502	10658	10900	10802	9018

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. t statistics are shown in parentheses. The dependent variable is the survival dummy variable, which equals one if the borrowing-lending relationship continues in year t, otherwise zero. This table shows the estimation result of the model with industry fixed effects. We also include 5-year moving average values of firm ROA, interest coverage ratio, book leverage ratio, and size to control for time-varying firm fixed effects. The estimated coefficients are not shown in the table.

B.2 Bank Loan Model with Time-invariant Bank Fixed Effects

In this paper, because our focus is on the risk-taking channel of conventional and unconventional monetary policy, we estimate the triple interaction effects, which show the heterogeneity in risky lending across banks with different levels of riskiness. In Appendix B, we address the double interaction effects of monetary policy shocks in terms of bank leverage. In other words, we study the difference in changes in loans from risky and non-risky banks to firms with average credit risks in response to monetary policy shocks. To do so, we estimate the following panel regression model with time-invariant bank and firm fixed effects as follows:

$$\begin{aligned}\Delta\mathrm{LOAN}_{ijt} = \quad & \mathrm{FirmFE}_{it} + \mathrm{BankFE}_j + \textstyle\sum_{k=1}^{3}(\delta_{3k}\mathrm{MP}_{kt} * \mathrm{BANK}_{jt-1}) \\ & + \gamma'\mathrm{CONTROL}_{ijt} + \epsilon_{ijt}, \end{aligned} \tag{B-1}$$

where BANK_{jt-1} is a proxy for the bank's balance sheet risk, such as the leverage ratio and liquidity ratio. FirmFE_{it} denotes the time-variant fixed effects of firm i and BankFE_j indicates the time-invariant those of bank j. $\mathrm{CONTROL}_{ijt}$ denotes a vector of the other control variables including the bank variables and interaction effects between the macroeconomic variables and the bank risk variable. More specifically, we include the five bank variables—the liquid assets ratio (BLIQ), bank size (BSIZE), the return on assets (BROA), the market leverage ratio (BMLEV), the government bonds holdings ratio (BJGB)—and the eight double interaction terms, which consist of the bank and macroeconomic variables. The bank variables include return on assets, bank size, market leverage ratio, and the macroeconomic variables include stock returns (RSTOCK), growth rate of real GDP, and consumption price index. To focus on the double interaction effects, we do not include the triple interaction terms in this model.

First, the estimation result shown in Table A.2 indicates that sound banks tend to increase loans more than not-sound ones do. In other words, banks with higher return on assets and a lower market leverage ratio are likely to increase bank loans.

Second, the double interaction term of monetary base shocks and the market leverage ratio is estimated to be significantly positive, which implies that banks with higher leverage ratios are more likely to increase lending in response to monetary base shocks. This result coincides with the finding of Baba et al. (2006) that mitigating the stress in the funding market for banks by increasing the monetary base helps banks increase loans. However, we emphasize that we do not find heterogeneous effects of the monetary base shocks in terms of the interaction effect with bank and firm risk.

On the contrary, the double interaction terms for the conventional monetary policy shock and composition shock with the market leverage ratio are not significantly different from zero. Given that the estimated triple interaction effects for these two shocks support the existence of the risk-taking channel, the heterogeneity in banks' risk really matter only for risky lending, not for average lending. These results provide a policymaker with the important implication that when implementing conventional policy in a low interest rate environment or increasing the risky assets ratio of the central bank's balance sheet, it should pay special attention not only to the aggregate growth rate of loans but also to the quality of bank loans. Furthermore, the double interaction effects for bank size and the composition shock is estimated to be significantly negative, which suggests that smaller banks respond more prominently to it, while those for the short-term rate and monetary base shock increase lending from larger banks more than that from smaller banks. This result also highlights the different effects of conventional and unconventional monetary policy shocks.

B.3 Estimation Results for the Probability of Firm's Bankruptcy and Distance-to-default

In Section 2.2.3, we introduced the distance-to-default dummy as a firm credit risk variable. In Appendix B.3, we show that distance-to-default can explain the probability of bankruptcy. To do so, we estimate the following simple probit

Table B.2: Estimation Result of Bank Lending Model for Double Interaction Effects of Monetary Policy Shocks and Bank Leverage

Dependent var.: $\Delta LOAN$	
Inverse Mills ratio	0.0815***
	(7.23)
Bank risk variable	
BROA	1.574***
	(3.71)
BSIZE	-0.229
	(-0.30)
BMLEV	-0.536***
	(-4.12)
Double interaction effects	
Monetary Policy with Bank Leverage	
SHORT*BMLEV	0.0312
	(0.37)
MB*BMLEV	0.289**
	(2.43)
COMP*BMLEV	0.130
	(1.39)
Monetary Policy with Bank size	
SHORT*BSIZE	0.471***
	(4.10)
MB*BSIZE	0.408***
	(3.57)
COMP*BSIZE	-0.500***
	(-4.34)
N	159781
Firm*year fixed effects	✓
Bank fixed effects	✓

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. t statistics based on robust standard errors are in parentheses. The dependent variable, . This table reports the estimation results of the model with firm*year and bank fixed effects shown in Equation (B-1), where the first log-difference of the outstanding amount of bank loan (multiplied by 100 for expression in percentage terms) is used as a dependent variable. $\mathrm{MB_t}$, $\mathrm{COMP_t}$, and $\mathrm{SHORT_t}$ indicate monetary base, composition and short term interest rates shocks, respectively. In the regression model, we also included the bank liquid assets ratio (BLIQ), the bank government bond holding ratio (BJGB), and the following ten double interaction terms: BSIZE*GDP, BROA*GDP, BSIZE*ROA, BROA*CPI, BSIZE*RSTOCK, BROA*RSTOCK, BROA*SHORT, BROA*MB,
BROA*COMP, BLEV*RSTOCK, where GDP, CPI and RSTOCK denote the change rate of real GDP, the consumer price index and the Nikkei 225 stock price index from t-2 to t-1, respectively. BSIZE and BROA denote the bank's size defined as the log of the total book assets and the bank's return on assets, respectively.

model:

$$Fail_{it} = \begin{cases} 1 & if\ y_{dt} = \alpha + \beta FLDD4_{it-1} + control_{it} + \epsilon_{it} > 0\ ,\ or \\ 0 & otherwise. \end{cases} \tag{B-2}$$

$Fail_{it}$ denotes firm i's bankruptcy indicator, which takes one if firm i goes bankrupt in fiscal year t and zero otherwise. ϵ_{it} denotes a disturbance term that follows the standard normal distribution. $control_{it}$ indicates the other control variables including the year dummies, the firm's return on assets, and the firm's book leverage ratio. Then, the probability of bankruptcy is described as follows:

$$Prob(Fail_{it} = 1) = \Phi(\alpha + \beta FLDD4_{it-1} + control_{it}) \tag{B-3}$$

where $\Phi(\cdot)$ indicates the cumulative distribution function of the standard normal distribution. The estimation result in Table B.3 indicates that a firm's lower distance-to-default is associated with a higher probability of bankruptcy, which provides us with evidence that the indicator allows us to capture credit risk well.

Table B.3: Estimation Result of Firm Bankruptcy Model

	(1)
Dependent var.: *Fail*	
FLLD4	0.706^{***}
	(7.36)
FROA	-0.00270
	(-1.50)
FBLEV	0.00547^{***}
	(4.42)
FSIZE	0.113^{***}
	(3.85)
year dummies	✓
N	29824

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively. t statistics are shown in parentheses. The table shows the estimation result of the probit model of firm bankruptcy based on Japanese listed firms from FY 1999 to 2014, where the dependent variable, the firm bankrupt indicator takes one if firm i goes bankruptcy in year t. The independent variables include the firm book leverage ratio, the firm return on assets, the firm size and year dummies at the end of fiscal year $t-1$ as control variables.

Appendix C
Chapter 3

C.1 Variance Decompositions with Lending Stance Shock

To investigate the contribution of bank loan supply shocks to the Japanese economy, I performed a variance decomposition analysis of forecast errors for each variable. However, more strict assumptions are required for a variance decomposition because we can only identify fundamental bank loan supply shocks up to a scale and sign. In this study, I conducted variance decompositions by assuming that s_t is perfectly correlated with the fundamental shocks μ_t. In this Appendix, I show more precisely how this assumption works in variance decompositions. Furthermore, I show that we can estimate the "lower bounds" of the contributions of loan supply shocks in variance decompositions that would be obtained without the perfect correlation assumption. Here, without loss of generality, I assume that the shock variable in reduced form VAR, ν_t, is a scalar. For variance decomposition, we need to decompose the variance of ν_t as follows:

$$Var(\nu_t) = B_1^2 Var(\mu_{1t}) + other, \tag{C-1}$$

where we are interested in the contribution of the fundamental loan supply shock, $B_1^2 Var(\mu_{1t})$. To calculate $B_1^2 Var(\mu_{1t})$, we calculate a linear projection of ν_t on s_t

as follows,

$$\nu_t = \pi s_t + e_t, \tag{C-2}$$

where

$$\pi = E(s_t \nu_t)/E(s_t^2) = \alpha B_1/E(s_t^2), \tag{C-3}$$

and e_t is a random variable with $E(e_t) = 0$. By the definition of α, we can have a linear projection of s_t on μ_{1t} as follows,

$$s_t = \frac{\alpha}{E(\mu_{1t}^2)} \mu_{1t} + \omega_t \tag{C-4}$$

where ω_t is a random variable with $E(\omega_t) = 0$. Therefore, by assuming $E(\mu_{1t}) = 0$, the variance of s_t can be written as follows:

$$Var(s_t) = \alpha^2/E(\mu_{1t}^2) + Var(\omega_t) \tag{C-5}$$

Hence,

$$Var(s_t) = E(s_t^2) \geq \alpha^2/E(\mu_{1t}^2) \tag{C-6}$$

On the other hand, by Equation (C-2), the contribution of lending stance shocks s_t can be calculated as follows,

$$Var(\nu_t) = \alpha^2 B_1^2/E(s_t^2) + Var(e_t). \tag{C-7}$$

Thereafter, we can show that the contribution of s_t to the variance of ν_t coincides with the lower bound of μ_{1t} as follows:

$$\begin{aligned} \alpha^2 B_1^2/E(s_t^2) &\leq \alpha^2 B_1^2 \frac{E(\mu_{1t}^2)}{\alpha^2} \\ &= B_1^2 E(\mu_{1t}^2) = B_1^2 Var(\mu_{1t}) \end{aligned} \tag{C-8}$$

Furthermore, if we assume that s_t is perfectly correlated with μ_{1t}, then $Var(s_t) = \alpha^2/E(\mu_{1t}^2)$ holds and the equality holds in Equation (C-8).

We can estimate the left hand side term, $\alpha^2 B_1^2/E(s_t^2)$, in equation (C-8). We can hereby use it as a proxy for the right hand side term $B_1^2 Var(\mu_{1t})$, which we need to calculate. Hence, by simply regressing ν_t on s_t, we can calculate the "lower bound" of the contribution of a fundamental bank loan supply shock on each variable's variance in the VAR system. The other procedure to calculate variance decomposition follows the standard method.

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