Risk-Taking Channel of Unconventional Monetary Policies in Bank Lending*

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ABSTRACT. We investigate 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. We 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.

JEL classification: E44, E52, G21

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1. Introduction  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 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

\(^1\) 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.

\(^2\) 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.
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)).

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) because of bank and firm balance sheet effects. 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.

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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.

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. 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 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 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

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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. 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 3 for more details on our identification strategy.
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)). Therefore, if we used only aggregate variables such as the monetary base 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. 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.

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 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.
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)).

In addition to banks’ balance sheet problems, 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. This previous research has

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9 Peek and Rosengren (2005) found heterogeneous lending behavior across Japanese financial 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
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 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)). 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 paper proceeds as follows. Section 2 introduces the datasets we analyze. Section 3 discusses the exogenous components of monetary policy. Section 4 explains our empirical identification strategy. Section 5 discusses the results and Section 6 concludes. Appendix A 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.

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 identity was not disclosed in their data, they did not control for firm characteristics.

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.
Appendix B provides the estimation results for the double interaction effects of monetary policy and the bank risk variable. Appendix C reports the estimation results for the probit model for firm bankruptcy to show that distance-to-default predicts the firm failure.

2. 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, we adopted two procedures according to the existence of lending activities from the succeeding bank after the bankruptcy or merger:

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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.
(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 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 provides the summary statistics for our loan-level matched data.

3. 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

\(^{13}\) 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.
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.\footnote{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.}

### 3.1. 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:

\[
X_t = \Lambda F_t + \epsilon_t ,
\]

where \( X_t = (x_{1t}, ..., x_{nt})' \) denotes the vector of the \( n \) financial time series, \( \epsilon_t \) indicates the vector of the \( n \) idiosyncratic disturbance terms, \( F_t \) is the vector of \( l \) unobserved common factor, and \( \Lambda \) is a matrix of the coefficients identified as factor loadings. We aim to extract common factors \( F_t \) 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), four yen interest swap rates (one, two, five, and 10 years), one forward rate (30-year JGBs), 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:

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

and for interest rates,

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

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.

\(^{16}\) 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.
By using the three principal components as instruments, that is, IV₁, IV₂, and IV₃, we extract the shocks from the conventional and unconventional monetary policy measures.¹⁷

3.2. **Exogenous Components of Monetary Policy** We use the three principal components as instrumental variables, IV₁, IV₂, and IV₃, 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 exploiting the forecast errors constructed from market-based expectations; that is, IV₁, IV₂, and IV₃ 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:

\[
\Delta SR_t = (\beta_{1s} + \gamma_{1s} D_t) IV_{1t} + (\beta_{2s} + \gamma_{2s} D_t) IV_{2t} + (\beta_{3s} + \gamma_{3s} D_t) IV_{3t} + \epsilon_{st},
\]

where \(\Delta SR_t\) 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 at-

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

\[
IV_{kt} = \sum_{h_i \in H_t} IV_{kh_{it}},
\]

where \(H_t\) indicates the set of days on which the monetary policy meeting is held in month \(t\) and \(IV_{kh_{it}}\) denotes the principal components of the two-day changes in financial asset prices after these monetary policy meeting days.
tributed 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 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)).

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:

\[
\Delta MB_t = \sum_{l=1}^{4} (\beta_{1ml} + \gamma_{1ml}D_t)IV_{1t}^l + \sum_{l=1}^{4} (\beta_{2ml} + \gamma_{2ml}D_t)IV_{2t}^l + \sum_{l=1}^{4} (\beta_{3ml} + \gamma_{3ml}D_t)IV_{3t}^l + \epsilon_{mt},
\]

where \(IV_{kt}^l \ (l = 1, \ldots, 4)\) 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

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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.
R-squared values in this first-stage instrumental variable regression (Christian 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.

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:

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

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. 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.

3.3. Monetary Policy Shocks We should also note that Figure 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. 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.

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 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 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.

4. 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.

4.1. 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 policy, focusing on its heterogeneous credit “allocation” effects owing to the heterogeneity in banks’ balance sheet risks.

\(^{20}\) 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.
Our baseline model with time-variant bank and firm fixed effects is specified as follows:

\[
\Delta \text{LOAN}_{ijt} = \sum_{k=1}^{3} (\delta_k \text{FIRM}_{it-1} \ast \text{BANK}_{jt-1} \ast \text{MP}_{kt}) + \text{FirmFE}_{it} + \text{BankFE}_{jt} + \gamma' \text{CONTROL}_{ijt} + \epsilon_{ijt},
\]

where \(\text{FIRM}_{it-1}\) is a risky firm indicator that takes one if firm \(i\) is categorized as one with high credit risk and zero otherwise. \(\text{BANK}_{jt-1}\) is a proxy for a bank’s balance sheet risk, such as the leverage ratio and the liquidity ratio. \(\text{FirmFE}_{it}\) and \(\text{BankFE}_{jt}\) 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. \(\text{CONTROL}_{ijt}\) 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 \(\text{FIRM}_{it-1} \ast \text{BANK}_{jt-1} \ast \text{MP}_{kt}\). 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 (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:

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

where \(\text{others}_1\) 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.\textsuperscript{22}

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

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

where others\textsubscript{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:

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

By estimating the interaction effects, we identify the heterogeneous effects of monetary policy shocks MP\textsubscript{kt} across the bank risk variable BANK\textsubscript{jt-1} on lending to risky firms identified by FIRM\textsubscript{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 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.\textsuperscript{23} Hence, the triple interaction

\textsuperscript{22} In Appendix B, 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).

\textsuperscript{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
effect captures the heterogeneous risk profile change in banks’ portfolios across those with different degrees of balance sheet risk.

Our baseline model (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.

4.1.1. **Monetary Policy Shocks and Interaction Terms** Equation (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 3. 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 ($FIRM_{it−1} \times BANK_{jt−1} \times MP_{kt}, k = 1, 2, 3$) in the baseline model (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.

4.1.2. **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 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 (7).²⁴

²⁴ We estimate a bankruptcy model of a firm and the results are shown in Appendix C. The result indicates that our firm risk variable, distance-to-default, provides explanatory power for a firm’s bankruptcy.
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). In fact, in Appendix C, 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:

\[
DD = \ln \left( \frac{V_A}{D} \right) + \frac{\left( r - \frac{1}{2}\sigma_A^2 \right)}{\sigma_A},
\]

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 \(\sigma_A\) 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 \(\sigma_A\) 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 \((D)\). We calculate the market value of equity by multiplying the stock price at the end of year \(t - 1\) by the number of shares. To estimate the volatility of equity \((\sigma_E)\), 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. We use one-year JGBs for the risk-free rate \((r)\).

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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 \((\sigma_A)\). 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.

27 More specifically, we calculate the annualized estimated volatility of the market value of equity as
We rank firms’ credit risk by distance-to-default and construct a low distance-to-default indicator for the firm, \((FLDD_{i,t-1})\), 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.

### 4.1.3. 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 constraints) 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

\[
\sigma_{E, it} = \sqrt{\frac{1}{20 - 1} \times \sum_{k=d(t)-19}^{d(t)} (ret_k - \overline{ret}_{d(t)})^2 \times \sqrt{240}},
\]

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.  

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)
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 $100 \times \frac{\text{Book Value of Debt}}{\text{Market Value of Equity} + \text{Book Value of Debt}}$, 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 (FIRM$_{jt-1}$ * BMLEV$_{jt-1}$ * 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 to an accommodating composition shock than one with high capitalization. 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 de- 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.

29 We should note that positive monetary base and composition shocks mean monetary policy easing, while a positive short-term rate shock indicates tightening.
pending on their asset structure, we also include interaction terms for the liquid assets ratio \( \text{BLIQ}_{jt-1} \), 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 \( \text{BJGB}_{jt-1} \) and stock holdings \( \text{BSTOCK}_{jt-1} \). 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 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 respond 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.

4.1.4. Other Control Variables

We also include other control variables in the panel regression models. In particular, in addition to the main triple interaction variables \((\text{FIRM}_{t-1} \times \text{BANK}_{jt-1} \times \text{MP}_k)\) in Equation (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 (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.

4.2. 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.\footnote{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 $j$.} 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 A. 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.

5. 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.

5.1. **Risk-taking Channel** In this subsection, we report the estimation results of Equation (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.

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.

5.1.1. **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 (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.

5.1.2. 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 (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 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 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 3.

Table 4 summarizes our findings that the composition shocks are prone to stimulate lending from banks with lower liquid assets ratios.

5.1.3. 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 (BJGJB) instead of the liquid assets ratio as the bank risk variables.

The estimation result shown in column (2) of Table 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.

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

Column (3) in Table 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.

5.1.5. 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 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 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.\footnote{The estimation results for the coefficient on the triple interaction effects of the JGB and stock holding ration are not reported in Table 5.}

5.2. **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.

5.2.1. **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 4. This fact implies that the heterogeneity in the size of the capital gains 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 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, $BHO_{t-1}$, 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.\footnote{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 Yermili (2013) point out that this is associated with the bank’s risk management.}

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 6 indicates that the triple interaction effect of short-term rate shocks, the high other assets ratio dummy, and the firm risk variable ($\text{SHORT} \times BHO \times \text{FLDD4}$) 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 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, BHRHV\(_{t-1}\), 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 7 show a significantly negative estimate for the triple interaction term for the short-term rate shock (SHORT \(\times\) BHRHV \(\times\) FLDD4) and a significantly positive estimate for the composition shocks (COMP \(\times\) BHRHV \(\times\) 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.

5.2.2. 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 4 to 7. However, this does not exclude the possibility of its affecting bank lending homogeneously. In fact, in Appendix B, 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.
5.2.3. **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 4 and 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 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 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 4 and 7.

5.2.4. **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 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 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

\(^{34}\) 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.
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 3 (see also the result shown in Appendix C), 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.\footnote{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 $t$.}

This result suggests that higher credit risk or lower distance-to-default is not necessarily associated with higher interest payments.\footnote{Using the distance-to-default instead of its dummy variable does not change the result qualitatively.} 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.

6. 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 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.

Appendix A: Estimation Results for Relation Survival Probability In Section 5, 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 4, 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 A.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.

Appendix B: 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:

\[
\Delta \text{LOAN}_{ijt} = \text{FirmFE}_{it} + \text{BankFE}_{j} + \sum_{k=1}^{3} (\delta_k \text{MP}_{kt} \ast \text{BANK}_{jt-1}) \\
+ \gamma^t \text{CONTROL}_{ijt} + \epsilon_{ijt},
\]  

(A-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. 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.

Appendix C: Estimation Results for the Probability of Firm’s Bankruptcy and Distance-to-default  In Section 3, we introduced the distance-to-default dummy as a firm credit risk variable. In Appendix C, we show that distance-to-default can explain the probability of bankruptcy. To do so, we estimate the following simple probit model:
\[ \text{Fail}_t = 1 \quad \text{if} \quad y_t = \alpha + \beta FLDD_{4t-1} + \text{control}_t + \epsilon_t > 0, \quad \text{or} \]
\[ 0 \quad \text{otherwise}. \]  

(A-2)

\( \text{Fail}_t \) denotes firm \( i \)'s bankruptcy indicator, which takes one if firm \( i \) goes bankrupt in fiscal year \( t \) and zero otherwise. \( \epsilon_t \) denotes a disturbance term that follows the standard normal distribution. \( \text{control}_t \) 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:

\[ \text{Prob}(\text{Fail}_t = 1) = \Phi(\alpha + \beta FLDD_{4t-1} + \text{control}_t) \]  

(A-3)

where \( \Phi(\cdot) \) indicates the cumulative distribution function of the standard normal distribution. The estimation result in Table A.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.
REFERENCES


[76] Stein, J. C., 2013, Yield-Oriented Investors and the Monetary Transmission Mechanism, Remarks at Banking, Liquidity and Monetary Policy, a Symposium Sponsored by the Center of Financial Studies in Honor of Raghuram Rajan.


Figure 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.
Figure 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 1–4 quarterly lagged monetary policy surprises, respectively. Each series is summarized on a fiscal year basis.
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 1–4 quarterly lagged monetary policy surprises, respectively. Each shock is summarized on a fiscal year basis.
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Notes: This table shows annual sample averages of the number of observations for borrowing firms, lending banks, and lending–borrowing relationships.
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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.
Table 3: Estimation Result of Baseline Bank Lending Model

<table>
<thead>
<tr>
<th>Monetary policy shocks</th>
<th>Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>SHORT<em>BMLEV</em>FLDD4</td>
<td>-0.260*</td>
</tr>
<tr>
<td></td>
<td>(0.151)</td>
</tr>
<tr>
<td>MB<em>BMLEV</em>FLDD4</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>(0.229)</td>
</tr>
<tr>
<td>COMP<em>BMLEV</em>FLDD4</td>
<td>0.0342</td>
</tr>
<tr>
<td></td>
<td>(0.172)</td>
</tr>
</tbody>
</table>

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% |

<table>
<thead>
<tr>
<th>Macroeconomic variables</th>
<th>Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP<em>BMLEV</em>FLDD4</td>
<td>-0.185*</td>
</tr>
<tr>
<td></td>
<td>(0.0987)</td>
</tr>
<tr>
<td>CPI<em>BMLEV</em>FLDD4</td>
<td>-0.254</td>
</tr>
<tr>
<td></td>
<td>(0.333)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Other control variables</th>
<th>Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inverse Mills Ratio</td>
<td>0.473***</td>
</tr>
<tr>
<td></td>
<td>(0.0214)</td>
</tr>
<tr>
<td>SHORT<em>BROA</em>FLDD4</td>
<td>-0.708</td>
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<tr>
<td></td>
<td>(0.771)</td>
</tr>
<tr>
<td>MB<em>BROA</em>FLDD4</td>
<td>0.182</td>
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<td>(1.056)</td>
</tr>
<tr>
<td>COMP<em>BROA</em>FLDD4</td>
<td>-1.193</td>
</tr>
<tr>
<td></td>
<td>(0.844)</td>
</tr>
<tr>
<td>SHORT<em>BSIZE</em>FLDD4</td>
<td>-0.278</td>
</tr>
<tr>
<td></td>
<td>(0.223)</td>
</tr>
<tr>
<td>MB<em>BSIZE</em>FLDD4</td>
<td>-0.0335</td>
</tr>
<tr>
<td></td>
<td>(0.235)</td>
</tr>
<tr>
<td>COMP<em>BSIZE</em>FLDD4</td>
<td>-0.738***</td>
</tr>
<tr>
<td></td>
<td>(0.228)</td>
</tr>
</tbody>
</table>

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.
Table 4: Estimation Results with Bank Assets

<table>
<thead>
<tr>
<th>Liquid Assets</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SHORT<em>BLIQ</em>FLDD4</td>
<td>0.0112</td>
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<td>(0.0489)</td>
</tr>
<tr>
<td>MB<em>BLIQ</em>FLDD4</td>
<td>0.0133</td>
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<td>(0.0621)</td>
</tr>
<tr>
<td>COMP<em>BLIQ</em>FLDD4</td>
<td>-0.0862*</td>
<td></td>
<td>(0.0477)</td>
</tr>
</tbody>
</table>

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)   |

Stocks

| SHORT*BSTOCK*FLDD4           | -0.271     |            | (0.173)    |
| MB*BSTOCK*FLDD4              | 0.271      |            | (0.281)    |
| COMP*BSTOCK*FLDD4            | 0.263      |            | (0.192)    |

<table>
<thead>
<tr>
<th>N</th>
<th>176181</th>
<th>186909</th>
<th>186909</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm * Year fixed effect</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Bank * Year fixed effect</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

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.

MB_t, COMP_t, and SHORT_t indicate monetary base, composition and short term interest rates shocks, respectively. Increases in MB_t and COMP_t indicates an increase in monetary base and risky asset ratio held by the Bank of Japan, respectively. An increase in 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 5.
Table 5: Estimation Results with the Real Estate Industry Dummy Variable

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. Variable: $\Delta LOAN$</td>
<td>BANK= BMLEV</td>
<td>BANK= BNPL</td>
</tr>
<tr>
<td>Monetary policy shocks</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SHORT<em>BANK</em>ESTATE</td>
<td>-0.385</td>
<td>-1.223&quot;</td>
</tr>
<tr>
<td></td>
<td>(0.398)</td>
<td>(0.559)</td>
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<tr>
<td>MB<em>BANK</em>ESTATE</td>
<td>-0.599</td>
<td>0.859</td>
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<tr>
<td></td>
<td>(0.613)</td>
<td>(0.877)</td>
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<tr>
<td>COMP<em>BANK</em>ESTATE</td>
<td>0.636</td>
<td>0.211</td>
</tr>
<tr>
<td></td>
<td>(0.516)</td>
<td>(0.629)</td>
</tr>
<tr>
<td>Macroeconomic variable</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP<em>BANK</em>ESTATE</td>
<td>-0.438*</td>
<td>-0.0816</td>
</tr>
<tr>
<td></td>
<td>(0.250)</td>
<td>(0.327)</td>
</tr>
<tr>
<td>CPI<em>BANK</em>ESTATE</td>
<td>-0.122</td>
<td>-0.355</td>
</tr>
<tr>
<td></td>
<td>(0.897)</td>
<td>(0.900)</td>
</tr>
</tbody>
</table>

| 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.

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. The first and second columns specify the estimation result with the bank capital buffer and bank non-performing ratio, 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.

BANK indicates the bank capital buffers and the non-performing loan ration for column (1) and (2) respectively.

BMLEV indicates the bank market leverage ratio. BNPL indicate the non-performing loan ratio, expressed in percentage terms. 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 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.
Table 6: Estimation Results with High Alternative Assets Ratio Bank Dummy

<table>
<thead>
<tr>
<th>Monetary policy interaction terms</th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SHORT<em>BHO</em>FLDD4</td>
<td>-1.321**</td>
</tr>
<tr>
<td>MB<em>BHO</em>FLDD4</td>
<td>0.783</td>
</tr>
<tr>
<td>COMP<em>BHO</em>FLDD4</td>
<td>-0.234</td>
</tr>
<tr>
<td>N</td>
<td>187168</td>
</tr>
</tbody>
</table>

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 ratio 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.
Table 7: Estimation Results with the Bank Dummy for High Return and High Risk Portfolio

<table>
<thead>
<tr>
<th>Monetary policy interaction terms</th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SHORT<em>BHRHV</em>FLDD4</td>
<td>-2.154*</td>
</tr>
<tr>
<td></td>
<td>(1.183)</td>
</tr>
<tr>
<td>MB<em>BHRHV</em>FLDD4</td>
<td>-0.229</td>
</tr>
<tr>
<td></td>
<td>(0.949)</td>
</tr>
<tr>
<td>COMP<em>BHRHV</em>FLDD4</td>
<td>1.596**</td>
</tr>
<tr>
<td></td>
<td>(0.744)</td>
</tr>
<tr>
<td>N</td>
<td>187168</td>
</tr>
</tbody>
</table>

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 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.
Table 8: Estimation Results with Loan to Deposit Ratio

<table>
<thead>
<tr>
<th>Monetary policy interaction terms</th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SHORT<em>BLD</em>FLDD4</td>
<td>0.00578</td>
</tr>
<tr>
<td></td>
<td>(0.0100)</td>
</tr>
<tr>
<td>MB<em>BLD</em>FLDD4</td>
<td>-0.00543</td>
</tr>
<tr>
<td></td>
<td>(0.0116)</td>
</tr>
<tr>
<td>COMP<em>BLD</em>FLDD4</td>
<td>0.0137*</td>
</tr>
<tr>
<td></td>
<td>(0.00749)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>173203</td>
</tr>
</tbody>
</table>

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.
Table 9: Estimation Result for Interest Rate Gaps Regression

|                | Interest Rate Gap  
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>FLDD4</td>
<td>-0.00110 (0.00141)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>35440</td>
</tr>
</tbody>
</table>

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 calculated by following Hoshi and Cabarello (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,

\[ GAP_{it} = \beta FLDD4_{it} + YearFE_{it} + e_{it}, \]  

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

<table>
<thead>
<tr>
<th>Fiscal Year</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tbody>
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Notes: *** indicates 1%, * indicates 5%, and ** indicates 10% levels of significance, respectively. 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 A.2: Estimation Result of Bank Lending Model for Double Interaction Effects of Monetary Policy Shocks and Bank Leverage

<table>
<thead>
<tr>
<th>(1)</th>
<th>Dependent var.: $\Delta LOAN$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inverse Mills ratio</td>
<td>0.0815*** (7.23)</td>
</tr>
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</table>

Bank risk variable

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<tr>
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<tbody>
<tr>
<td>BROA</td>
<td>1.574*** (3.71)</td>
</tr>
<tr>
<td>BSIZE</td>
<td>-0.229 (-0.30)</td>
</tr>
<tr>
<td>BMLEV</td>
<td>-0.536*** (-4.12)</td>
</tr>
</tbody>
</table>

Double interaction effects

**Monetary Policy with Bank Leverage**

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<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>SHORT*BMLEV</td>
<td>0.0312 (0.37)</td>
</tr>
<tr>
<td>MB*BMLEV</td>
<td>0.289** (2.43)</td>
</tr>
<tr>
<td>COMP*BMLEV</td>
<td>0.130 (1.39)</td>
</tr>
</tbody>
</table>

**Monetary Policy with Bank size**

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</thead>
<tbody>
<tr>
<td>SHORT*BSIZE</td>
<td>0.471*** (4.10)</td>
</tr>
<tr>
<td>MB*BSIZE</td>
<td>0.408*** (3.57)</td>
</tr>
<tr>
<td>COMP*BSIZE</td>
<td>-0.500*** (-4.34)</td>
</tr>
</tbody>
</table>

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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, the first log-difference of the outstanding amount of bank loan, is multiplied by 100 for expression in percentage terms.

This table reports the estimation results of the model with firm*year and bank fixed effects shown in Equation (A-1).

$MB_t$, $COMP_t$, and $SHORT_t$ indicate monetary base, composition and short term interest rates shocks, respectively. Increases in $MB_t$ and $COMP_t$ indicates increases in the monetary base and risky asset ratio held by the Bank of Japan, respectively. An increase in $SHORT_t$ means an increase in short term interest rates.

$BMLEV$ indicates the bank market leverage ratio. 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 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.
Table A.3: Estimation Result of Firm Bankruptcy Model

<table>
<thead>
<tr>
<th>(1)</th>
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</thead>
<tbody>
<tr>
<td>Dependent var.: Fail</td>
<td>FLLD4</td>
<td>0.706***</td>
<td>(7.36)</td>
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</tr>
<tr>
<td></td>
<td>FROA</td>
<td>-0.00270</td>
<td>(-1.50)</td>
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<tr>
<td></td>
<td>FBLEV</td>
<td>0.00547***</td>
<td>(4.42)</td>
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</tr>
<tr>
<td></td>
<td>FSIZE</td>
<td>0.113***</td>
<td>(3.85)</td>
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<td></td>
<td>year dummies</td>
<td>✓</td>
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<td>N</td>
<td>29824</td>
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</tbody>
</table>

$t$ statistics in parentheses

Notes: ***, **, * indicate 1%, 5% and 10% levels of significance, respectively.

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.