



Bank of Japan Working Paper Series

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No.26-E-8
May 2026

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How Do Floods Affect Banks' Financial Conditions?

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Kakuho Furukawa[†], Komei Suzuki[‡]

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Abstract

This paper investigates the impact of flood disasters on banks' financial conditions. Using granular, municipality-level data from Japan, we exploit exogenous variation in the timing and location of floods to identify how the effects of these flood events are transmitted to banks' balance sheets. We find that flood exposure impairs asset quality and profitability, evidenced by elevated non-performing loan ratios and credit cost ratios alongside reduced returns on assets. However, the estimated magnitudes of the impairments are economically small relative to their average level, suggesting that the impact of floods on banks' financial conditions has been quantitatively limited thus far. Simultaneously, banks expand credit supply in affected regions following floods, possibly reflecting heightened credit demand of firms and households, driven by reconstruction and liquidity needs. In addition, we observe that the responses of variables are heterogeneous: banks exposed to regions where land prices decline sharply following floods experience larger declines in financial performance and a more muted expansion of credit. These observations are further pronounced for banks with a high proportion of their total lending secured by real estate. Our findings suggest that the depreciation of collateral value can also be an important transmission channel of climate-related physical risks to the banking sector.

JEL classification: G21, Q54, R33

Keywords: natural disasters; climate change; bank stability; credit supply; collateral channel

^{*} We would like to thank Takeo Hoshi, Jouchi Nakajima, and colleagues at the Bank of Japan especially Ichiro Fukunaga, Wataru Hirata, Takushi Kurozumi, Nao Sudo, and Azusa Takeyama for their valuable comments and discussions. The views expressed in this paper are those of the authors and do not necessarily reflect the official view of the Bank of Japan or of the Financial System and Bank Examination Department. Any remaining errors are those of the authors.

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1. Introduction

As the frequency and severity of weather-related disasters have escalated in recent years, their economic consequences and subsequent transmission to the banking system have attracted increasing attention from both policymakers and academics. For instance, global economic losses attributable to weather-related disasters are estimated to have exceeded USD 200 billion in 2024 (CRED, 2025). From a theoretical perspective, such damage may weaken banks' financial conditions through deteriorating economic performance of borrowers as a result of, for example, impairments to production facilities or dampened local economic activity and through declines in collateral values, potentially resulting in reduced credit supply due to tighter borrowing constraints (Batten et al., 2016; Bolton et al., 2020). However, there are also offsetting factors: banks may undertake ex-ante risk-mitigating actions, such as reallocating lending away from disaster-prone areas or increasing loan loss provisions in advance, while post-disaster reconstruction activity may trigger an increase in credit demand. Since these competing forces operate simultaneously, the overall impact of weather-related disasters on banks remains an empirical question.

Against this backdrop, this study examines the impact of floods on the financial condition of banks in Japan. We construct a novel and comprehensive dataset that combines information on financial statements and branch locations of approximately 300 banks with all flood damage over the past 25 years recorded at the municipality level, sourced from the Japanese government's *Flood Statistics*. The analysis proceeds in two steps. First, we assess whether floods affect banks' financial conditions. In this step, we estimate the average impact of floods on banks without explicitly considering specific transmission channels, such as a deterioration in borrowers' economic performance or a decline in collateral values. Second, we explicitly examine how the latter channel—a decline in collateral values following floods—operates as a transmission mechanism, which we term the *collateral channel*. Under this channel, a reduction in collateral values leads to a potential increase in credit costs, leading to a deterioration in borrowers' economic activity, as banks are required to recognize higher loan loss provisions to account for the deteriorating recovery value of their secured loans.¹ This channel posits that declines in the value of assets pledged as collateral reduce borrowers' net worth and borrowing capacity, thereby tightening their credit constraints (Bernanke et al., 1999; Kiyotaki and Moore, 1997). To test the presence of this channel, we examine whether banks with greater lending exposure to areas where

¹ Indeed, Cella and Schubert (2026) find that when Swedish banks revise collateral values following weather shocks, they typically revise them downward.

land prices decline more following a flood experience higher credit costs and more severe balance sheet constraints, even after controlling for their overall exposure to flooding.

The main findings are as follows. First, floods adversely affect banks' financial conditions, as evidenced by higher non-performing loan (NPL) ratios, higher credit cost ratios, and lower returns on assets (ROA), while simultaneously increasing credit supply. These results are robust to different specifications commonly employed in the literature. However, the estimated magnitudes are economically small relative to their sample means, suggesting that their impact on banks' financial conditions has been quantitatively limited thus far. Second, banks exposed to regions where land prices decline more sharply following flood damage experience more pronounced deteriorations in these financial indicators and a more constrained expansion of credit. These effects are further amplified for banks with a high proportion of their total lending secured by real estate, though flood events as a whole appear to increase banks' credit supply. Taken together, these findings provide evidence consistent with the operation of the collateral channel.

This paper contributes to the literature in two respects. First, it provides new evidence on the effects of weather-related hazards on banks in Japan. While the existing literature has expanded in recent years, most previous studies that focus on developed countries rely on data from the United States or Germany. This study extends the geographical scope of the evidence, confirming that the impact of floods on the banking sector is robust to different institutional and economic environments. Second, to the best of our knowledge, this paper is the first to explicitly examine the collateral channel as a transmission mechanism linking floods to bank outcomes empirically. Identifying not only the aggregate effects but also the underlying transmission mechanisms of floods is critical for effective risk management by banks and policymakers.²

The remainder of this paper is structured as follows: Section 2 introduces the literature relevant to this study. Section 3 describes the data used in our analysis. Section 4 shows our empirical models for testing the overall impacts of flood damage on banks and their estimation results. Section 5 further studies whether the collateral channel operates as a transmission channel linking flood damage to banks. Finally, Section 6 concludes the paper.

² Indeed, policymakers worldwide have issued guidelines on climate-related financial risks, including flood damage, which emphasize distinct transmission channels and corresponding supervisory responses (BCBS, 2022).

2. Related literature

2.1 Effects on the real economy and real estate prices

Assessing the effects of floods on banks requires an understanding of their impacts on the real economy and on the prices of assets pledged as collateral, particularly real estate. Theoretical predictions regarding the real economic effects of floods are ambiguous. Floods may depress economic activity through physical damage to production facilities and disruptions to business operations, but they may also stimulate activity through increased production to meet reconstruction demand following the flood. Consistent with this ambiguity, the empirical literature documents mixed results. While many cross-country studies report negative impacts of natural disasters on GDP, these effects appear attenuated in high-income and highly insured regions (Noy, 2009; Strobl, 2011; von Peter et al., 2012; Bello, 2017). At the firm level, evidence from Japan, New Zealand, and Europe indicates that floods could reduce the profitability of affected firms (Yamamoto and Naka, 2021; Prieto and Noy, 2024; Barbaglia et al., 2023). By contrast, other studies find that severe flood events in Europe could have increased firms' productivity, value added, and sales (Leiter et al., 2009; Coelli and Manasse, 2014; Noth and Rehbein, 2019).³ The effects also vary across sectors, with evidence, for example, suggesting that the construction sector may in fact see higher post-disaster reconstruction demand (Yamamoto and Naka, 2021; Ashizawa et al., 2022).

With respect to real estate markets, the literature consistently documents significant declines in property prices following flood exposure, whether direct or indirect (Contat et al., 2024; Fisher and Rutledge, 2021; Gibson and Mullins, 2020; Ortega and Taşpınar, 2018; Pommeranz and Steininger, 2020; Yi and Choi, 2020). However, the magnitude of these effects exhibits substantial regional heterogeneity. Price declines tend to be larger in areas where flood risk had not been fully capitalized prior to the event. For example, Holtermans et al. (2024) show that properties inundated during Hurricanes Harvey and Sandy experienced larger price declines in locations with lower ex-ante perceptions of flood risk. Similarly, evidence from Japan indicates that regions previously designated as high-risk on hazard maps or frequently exposed to severe flooding exhibit smaller declines in property values following flood events (Inoue and Komori, 2017; Koide et al., 2022). Maruyama et al. (2026) study changes in land prices in areas affected by Typhoon Hagibis in 2019 and find that the spillover effect of the flood event was more pronounced

³ Leiter et al. (2009), Coelli and Manasse (2014), and Noth and Rehbein (2019) examine the impacts of floods in Western Europe during the autumn of 2000, the 2010 flood in Veneto, Italy, and the 2013 flooding of the Elbe River in Germany, respectively.

in areas outside designated hazard maps. [Aiba and Hasegawa \(2025\)](#) examine the response of condominium prices following Typhoon Hagibis and show that property values declined for upper-floor units that experienced unexpected damage through electrical systems, but not for lower-floor units. They argue that flood risk had already been priced in for lower-floor units, where exposure was more salient *ex ante*.

2.2 Effects on banks

We next review the growing literature examining the effects of natural disasters on banks' financial conditions. The existing evidence indicates that the impact of floods on banks is heterogeneous and depends on institutional characteristics and the outcome measures considered. Using data from the United States, several studies document that severe weather-related disasters weaken banks' financial conditions across multiple dimensions, including lower Z-scores, higher default probabilities, increases in non-performing assets, declines in profitability, and declines in equity ratios ([Noth and Schüwer, 2023](#); [Do et al., 2023](#); [Apergis, 2023](#); [Blickle et al., 2021](#); [Petkov, 2022](#); [Walker et al., 2023](#)). However, some studies argue that these effects are confined to specific types of banks. For example, [Blickle et al. \(2021\)](#) show that negative stability effects—measured by capital ratios and Z-scores—are concentrated among single-county banks, while multi-county banks remain largely unaffected. Similarly, [Petkov \(2022\)](#) finds that severe hurricanes are associated with loan defaults at local banks but not at non-local institutions. Evidence from the 2013 Elbe River floods in Germany further suggests that locally oriented banks operating in directly affected regions experienced elevated credit risk, whereas banks located outside the affected areas but connected to flooded firms did not experience such changes due to their ability to diversify risks arising from local disasters ([Koetter et al., 2020](#); [Shala and Schumacher, 2024](#)).

Regarding credit supply, many previous studies find that banks in developed economies respond to natural hazard shocks by expanding lending ([Peters, 2025](#); [Cortés and Strahan, 2017](#); [Schüwer et al., 2019](#); [Koetter et al., 2020](#)), consistent with increased post-disaster credit demand ([Berg and Schrader, 2012](#); [Collier et al., 2021](#); [Ivanov et al., 2022](#)).⁴ In contrast, evidence from large-scale earthquakes—other major natural disasters in Japan—suggests that such shocks may also constrain credit supply. [Uesugi et al. \(2025\)](#) show that damage to firms' tangible assets and to the net worth of their main banks increased the likelihood of firms becoming credit constrained after the 2011 Great East Japan Earthquake. Similarly, [Hosono et al. \(2016\)](#) find that the impaired

⁴ One notable exception is [Gallagher and Hartley \(2017\)](#), who study household borrowing following Hurricane Katrina in 2005 and find a contraction in loan balances. They attribute this response to insurance payouts, which reduced post-disaster borrowing needs.

lending capacity of damaged banks exacerbated borrowing constraints for undamaged client firms following the 1995 Great Hanshin–Awaji Earthquake. Together, these findings indicate that the net effect of natural disasters on credit supply reflects the interaction between heightened borrowers' credit demand and tighter borrowing constraints arising from collateral value deterioration. The relative strength of these opposing forces is likely to depend on the sensitivity of collateral values to natural hazards and banks' reliance on real estate as loan collateral. While these previous studies focus on large-scale earthquakes, the underlying mechanism—namely, the erosion of collateral value—is likely also relevant to flood disasters.

A closely related study is [Ogura et al. \(2022\)](#), which analyzes the effects of severe floods on small businesses in Japan and finds that bank lending increases for firms located in flooded areas but declines for firms that incur direct physical damage, which they argue may be explained by the existence of the collateral channel. Furthermore, they report no significant effects of floods on aggregate bank credit supply or NPL ratios.

3. Data

Our flood damage data are obtained from the *Flood Statistics* published by Japan's Ministry of Land, Infrastructure, Transport and Tourism (MLIT). These statistics document flood-related damage at the municipality level on an annual basis, including the number of destroyed buildings and monetary losses.⁵ The data classify damage into three categories: (i) general assets, encompassing households, firms, and farmland; (ii) public infrastructure, such as roads, bridges, and river and coastal levees; and (iii) public services, including railways, water supply, and electricity networks. This study uses data on damage to general assets, which capture both direct property losses and costs associated with operational disruptions.⁶ Figure 1 presents the time series of total flood damage to general assets, while Figure 2 illustrates the geographical distribution of damage. The figures show that the total value of damage is dispersed nationwide rather than concentrated in a small number of regions.

Bank-level data are obtained from two primary sources. The first consists of individual banks'

⁵ Specifically, the statistics cover the following types of water-related disasters: (i) floods and inundation caused by river discharge; (ii) coastal inundation caused by storm surges and tsunamis; and (iii) mudflows, landslides, and slope failures caused by heavy rainfall. Other major disasters, such as earthquakes and windstorms, are not covered.

⁶ These costs are estimated based on the number of damaged buildings by degree of destruction. We exclude damage to public infrastructure and public services because such damage often generates spillovers beyond municipal boundaries. For example, damage to water supply infrastructure in one municipality may disrupt service provision in neighboring municipalities.

financial statements, which report balance sheet and income statement information as of the end of March each year, reflecting Japan's fiscal year-end. From these statements, we construct the NPL ratio, credit cost ratio, ROA, and total outstanding loans as dependent variables. The first three measures are available at the bank level, whereas loan volumes are observed at the bank–prefecture level.⁷

Figure 1. Flood damage in Japan

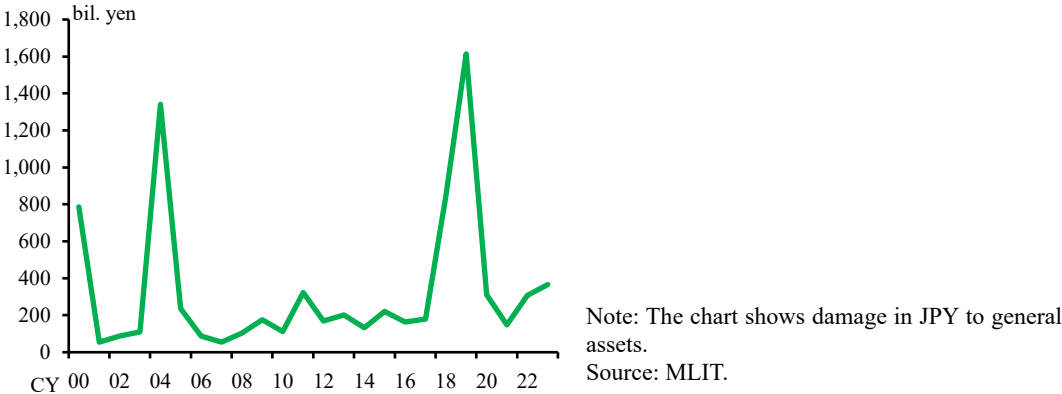
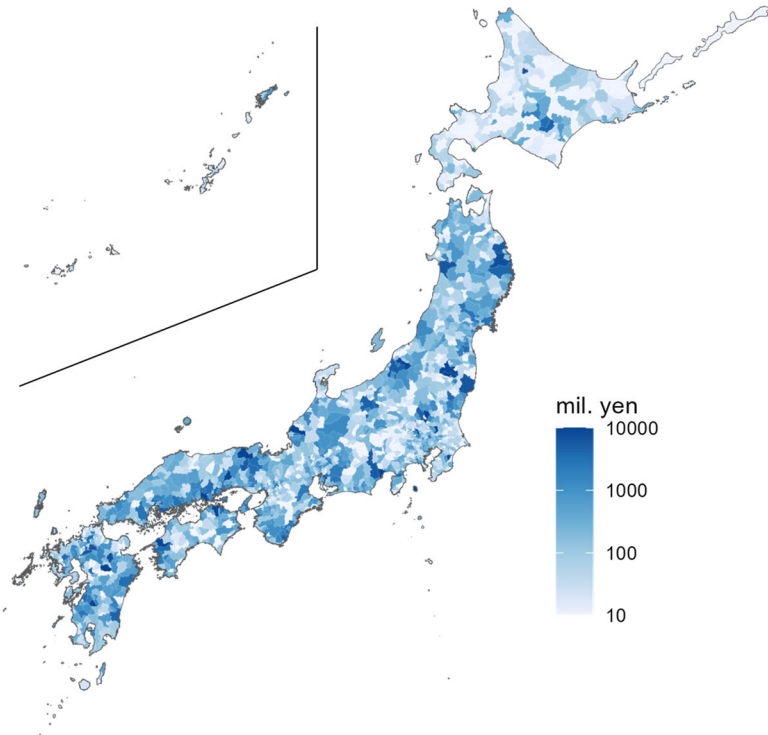


Figure 2. Geographical distribution of flood damage in Japan



Note: Color shows average yearly damages to general assets between 2000 and 2023.
Source: MLIT.

⁷ Japan has a two-tier local government system. The upper tier consists of prefectures, which serve as broad regional authorities. Each prefecture is further subdivided into municipalities (cities, towns, and villages), which function as the lower-tier, basic units of local administration. Every municipality is geographically nested within a specific prefecture. There are 47 prefectures and approximately 1,800 municipalities.

The second source is the Japan Financial Directory (*Nihon Kinyu Meikan*), published by Nikkin, which provides annual information on the location of all bank branches. We merge these data with banks' financial statements to estimate outstanding loans at the bank-municipality level. Specifically, we allocate bank i 's prefecture-level loans in year t across municipalities within the prefecture in proportion to the number of its branches, such that the estimated loan volume in municipality m equals prefecture-level loans multiplied by the share of the number of branches located in m . The equation is given as follows:

$$loan_{i,m,t} = loan_{i,p,t} \times \frac{\text{Number of branches}_{i,m,t}}{\text{Number of branches}_{i,p,t}} \quad (1)$$

Hereafter, subscripts p and m denote prefecture- and municipality-level variables, respectively. Although this approach relies on a simplifying assumption, it yields accurate approximations of actual lending patterns.⁸ Our sample comprises 292 banks, including mega banks, regional banks, and *shinkin* banks.⁹ The sample period is between FY2001 and FY2023.

The spatial granularity of our data is comparable to that employed in previous studies. In the United States, most analyses rely on the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which reports disaster damage at the county level based on insurer reports and meteorological records. Studies of the Elbe River floods similarly measure exposure at the German county (Landkreis) level. The average population of these administrative units corresponds to approximately 0.03% and 0.23% of the national populations in the United States and Germany, respectively. By comparison, the average Japanese municipality accounts for about 0.05% of the national population. On the banking side, existing studies likewise infer disaster exposure using bank location data, as more geographically disaggregated balance-sheet information is typically unavailable.

Table 1 reports descriptive statistics for the bank- and bank-prefecture-level variables. The distributions of NPL ratio, credit cost ratio, and ROA exhibit several extreme observations concentrated in the early 2000s, reflecting the resolution of NPLs stemming from Japan's financial crisis in the late-1990s. On average, almost 40% of a bank's branches are located in municipalities hit by floods each year, indicating that floods are not rare but rather common and relevant events

⁸ The correlation coefficient between supervisory loan-level data for a subset of regional banks and our estimated data is 0.88 for end-March 2024.

⁹ To ensure data continuity, we account for bank mergers by aggregating pre-merger entities and treating them as a single consolidated institution throughout the sample period. Banks involved in mergers with institutions lacking available financial statements are excluded.

for the average bank. Consistent with standard practice in the literature, we mitigate the influence of outliers by applying a two-sided 1% winsorization to the bank performance metrics.

Table 1. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Bank level					
Loans (bil. yen)	6705	1587	7263	16	101139
NPL ratio (%)	6705	5.70	3.59	0.12	27.29
Credit cost ratio (%)	6705	0.32	0.60	-3.66	17.13
ROA (%)	6705	0.12	0.42	-15.83	6.24
Real estate collateral ratio (%)	6705	29.83	14.98	0.40	85.57
Share of branches hit by floods (%)	6705	36.69	30.87	0.00	100.00
Bank-prefecture level					
Loan (bil. yen)	17876	529	2401	0	53458
Share of branches hit by floods (%)	17876	36.79	36.59	0.00	100.00

Note: The table reports descriptive statistics for the sample between FY2001 and FY2023.

4. The effects of floods on banks

4.1 Empirical strategies

We examine whether floods affect banks' financial conditions using two complementary empirical approaches. In both cases, we estimate regressions separately for bank-level and bank–prefecture–level outcomes.

In the first approach, we construct a binary indicator similar to [Do et al. \(2023\)](#) and [Ogura et al. \(2023\)](#) that captures banks' exposure to severe flood events. Specifically, for the bank-level (bank–prefecture–level) specification, the indicator $flood(q)_{i,t}$ ($flood(q)_{i,p,t}$) equals one if bank i operates at least one branch in municipalities (within prefecture p) whose flood damage per capita in year t exceeds the q -th percentile of the distribution across all municipalities over the sample period, and zero otherwise. We consider $q=90$ and 95 . The corresponding estimating equations are given by:

$$y_{i,t} = \beta flood(q)_{i,t-1} + \mu_i + v_t + \varepsilon_{i,t} \quad (2)$$

$$y_{i,p,t} = \beta flood(q)_{i,p,t-1} + \delta_{i,t} + \eta_{p,t} + \xi_{p,i} + \varepsilon_{i,p,t} \quad (3)$$

In the bank-level specification, μ_i and v_t denote bank and time fixed effects, respectively. In the bank–prefecture–level specification, we include bank–time fixed effects ($\delta_{i,t}$), prefecture–time fixed effects ($\eta_{p,t}$), and prefecture–bank fixed effects ($\xi_{p,i}$). Because the inclusion of bank–

time fixed effects absorbs all bank-level variation, banks operating exclusively within a single prefecture are excluded from this specification.

Identification relies on the assumption that the timing and geographic incidence of flood events are exogenous to banks' balance sheets and contemporaneous local economic conditions. This assumption is standard in the literature and is plausible over short- to medium-term horizons.¹⁰ The baseline specifications incorporate a single lag of flood exposure, reflecting prior evidence that flood effects are largely transitory (Do et al., 2023; Noth and Schüwer, 2023). Appendix A demonstrates that the results are robust to alternative lag structures. Our baseline specifications do not include additional time-varying control variables beyond fixed effects. This choice reflects the identifying assumption discussed above. The inclusion of bank-, time-, and region-specific fixed effects absorbs time-invariant heterogeneity across banks and regions as well as common macroeconomic shocks. Moreover, many candidate controls, such as local economic indicators or credit demand measures, are themselves affected by flood events and would therefore constitute post-treatment variables. Excluding such controls avoids bias arising from conditioning on outcomes of the treatment.

In the second approach, we construct a continuous measure of flood exposure, $Exposure_{i,t}$, following Noth and Schüwer (2023) and Blickle et al. (2021). This measure captures the total flood damage incurred by the borrowers of bank i in year t and is defined as:

$$Exposure_{i,t} = \log \left(\frac{1}{loan_{i,t}} \sum_m damage_{m,t} \times \frac{loan_{i,m,t}}{loan_{m,t}} \right) \quad (4)$$

where $damage_{m,t}$ denotes flood damage in municipality m in year t , $loan_{i,t}$ is the total outstanding loans of bank i , and $loan_{m,t}$ is the total volume of loans in municipality m . The bank-prefecture-level measure of flood exposure is likewise defined as:

$$Exposure_{i,p,t} = \log \left(\frac{1}{loan_{i,t}} \sum_{m \in p} damage_{m,t} \times \frac{loan_{i,m,t}}{loan_{m,t}} \right) \quad (5)$$

The corresponding estimating equations are:

¹⁰ Local economies may gradually adapt to recurrent flood risk through investments in protective infrastructure, such as embankments and dams, which could in principle bias our estimates. However, such projects typically require long planning and implementation horizons, and consequently previous studies do not treat this channel as a major concern for short- to medium-run analyses.

$$y_{i,t} = \beta Exposure_{i,t-1} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (6)$$

$$y_{i,p,t} = \beta Exposure_{i,p,t-1} + \delta_{i,t} + \eta_{p,t} + \xi_{p,i} + \varepsilon_{i,p,t} \quad (7)$$

4.2 Results

Tables 2 and 3 report the estimation results for Eq.(2)-(3) and Eq.(6)-(7), respectively. Using bank-level data, both approaches indicate that greater flood exposure is associated with statistically significant increases in NPL ratios and credit cost ratios, as well as declines in ROA, at conventional significance levels. These findings are consistent with evidence from the United States, although the estimated magnitudes are economically small. For example, Table 3 shows that banks experiencing a one-standard-deviation increase in flood damage exhibit increases in the NPL ratio and the credit cost ratio of approximately 0.06 percentage points and 0.01 percentage points, respectively, while also experiencing a reduction in ROA of approximately 0.01 percentage points. As of end-March 2025, the average NPL ratio, credit cost ratio, and ROA of the sample banks stood at 3.50 percent, 0.06 percent and 0.17 percent, respectively. Given that the estimated effects are marginal relative to these values, flood shocks have had limited impact on banks' financial conditions thus far.

Table 2. Estimation results with dummy explanatory variables

Variables	Bank level			Bank-prefecture level
	NPL ratio	Credit cost ratio	ROA	log(Loans)
	(1)	(2)	(3)	(4)
Severe floods defined as > 90th percentile				
flood(t-1)	0.16 *** (0.05)	0.03 ** (0.01)	-0.02 ** (0.01)	0.02 * (0.01)
Within R-sq	0.0017	0.0008	0.0008	0.0004
Severe floods defined as > 95th percentile				
flood(t-1)	0.06 (0.05)	0.02 (0.01)	-0.02 ** (0.01)	0.01 (0.00)
Within R-sq	0.0002	0.0003	0.0009	0.00003
Obs.	6703	6703	6703	13207
Bank FE	Y	Y	Y	N
Year FE	Y	Y	Y	N
Bank-Year FE	N	N	N	Y
Bank-Pref FE	N	N	N	Y
Pref-Year FE	N	N	N	Y

Note: The table reports regression results for Eq.(2) and Eq.(3). Dependent variable is indicated at the top of each column. The sample period is FY2001-FY2023. Standard errors clustered at the bank level (or bank-prefecture-level for log(Loans)) are presented in parentheses. The ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

At the bank–prefecture level, both tables show that flood exposure is associated with a statistically significant expansion of credit supply, consistent with previous studies. The estimated effect can be economically meaningful: Table 3 indicates that a one-standard-deviation increase in flood damage corresponds to an approximately 9% increase in lending.

Table 3. Estimation results with continuous explanatory variables

Variables	Bank level			Bank-prefecture level
	NPL ratio	Credit cost ratio	ROA	log(Loans)
	(1)	(2)	(3)	(4)
Exposure (t-1)	0.06 ** (0.03)	0.01 ** (0.01)	-0.01 ** (0.00)	0.09 *** (0.01)
Obs.	5556	5556	5556	8614
Within R-sq	0.001	0.001	0.001	0.023
Bank FE	Y	Y	Y	N
Year FE	Y	Y	Y	N
Bank-Year FE	N	N	N	Y
Bank-Pref FE	N	N	N	Y
Pref-Year FE	N	N	N	Y

Note: The table reports regression results for Eq.(6) and Eq.(7). Dependent variable is indicated at the top of each column. The sample period is FY2001-FY2023. The independent variables are standardized to have standard deviation of one. Standard errors clustered at the bank level (or bank-prefecture-level for log(Loans)) are presented in parentheses. The ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

5. The collateral channel of floods

5.1 Empirical strategies

We next examine whether the collateral channel operates as a transmission mechanism underlying the effects documented in the previous section. If this mechanism is present, it should generate heterogeneity in banks' responses to flood shocks along two dimensions. First, banks with significant lending exposure to regions where land prices are highly sensitive to flood damage are expected to experience a sharper increase in credit costs and tighter credit constraints on their clients. As discussed in Section 2, previous studies show that the extent to which land prices respond to flood damage can vary depending on whether flood risk has already been priced in. Second, banks with a higher share of loans secured by real estate should exhibit greater sensitivity to flood-induced declines in collateral values. We exploit these sources of heterogeneity to test for the presence of the collateral channel.

As an intermediate step, we verify whether heterogeneity in land-price responses to floods, as

documented in the literature, is present in our data. We estimate the following regression:

$$\Delta price_{m,t} = \gamma \log\left(\frac{damage_{m,t-1}}{pop_{m,t-1}}\right) + income_{m,t-1} + \mu_m + \nu_t + \varepsilon_{m,t} \quad (8)$$

where $\Delta price_{m,t}$ denotes the annual growth rate of land prices in municipality m as of January 1 in year t , based on data from MLIT; $damage_{m,t-1}$ measures flood damage to general assets; and $pop_{m,t-1}$ and $income_{m,t-1}$ denote population and taxable income per capita (in logs), respectively. Municipality and time fixed effects are denoted by μ_m and ν_t . Taxable income controls for time-varying local economic conditions affecting land prices.

We split municipalities into *Low-risk* and *High-risk* groups based on historical flood frequency. Municipalities experiencing fewer than five flood events over the sample period are classified as *Low-risk*.¹¹ Because flood risk is more likely to be capitalized into land prices in areas with frequent flooding (Inoue and Komori, 2017; Koide et al., 2022), we expect land prices to respond more strongly to flood damage in the *Low-risk* group. Table 4 confirms this prediction: flood damage has a statistically significant negative effect on land prices in *Low-risk* municipalities, while the effect is statistically insignificant in *High-risk* municipalities.

Table 4. Impacts of flood damage on land prices

Variables	All sample (1)	High risk (2)	Low risk (3)
Flood damage (t-1)	-0.01 ** (0.00)	0.00 (0.00)	-0.01 ** (0.00)
Income (t-1)	4.57 *** (0.85)	6.03 *** (1.60)	3.22 *** (1.01)
Obs.	31068	16191	14877
Within R-sq	0.008	0.011	0.005
Municipality FE	Y	Y	Y
Year FE	Y	Y	Y

Note: The table reports regression results for Eq.(8). The sample period is CY2001-CY2023. Standard errors clustered at the municipality level are presented in parentheses. The ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

Motivated by this result, we construct a measure capturing flood-induced declines in land prices in areas where banks extend credit:

¹¹ This threshold is set at the median number of flood occurrences experienced by municipalities over the sample period. We also used the 25th and 75th percentiles of flood occurrences but the results were largely unchanged.

$$LandPriceDamage_{i,t} = - \sum_m 1(m \in Low) \times \hat{\gamma}_L \log\left(\frac{damage_{m,t-1}}{pop_{m,t-1}}\right) \times \frac{loan_{i,m,t}}{loan_{i,t}} \quad (9)$$

where $1(m \in Low)$ is an indicator for *Low-risk* municipalities and $\hat{\gamma}_L$ is the estimated coefficient from the land-price regression for this group. The term $\hat{\gamma}_L \log(damage_{m,t-1}/pop_{m,t-1})$ represents the predicted land-price impact of flood damage. The resulting variable, $LandPriceDamage_{i,t}$, aggregates these impacts using lending weights. We reverse the sign of this variable so that higher values of $LandPriceDamage$ represent more severe negative shocks to collateral values.¹² Consistent with Table 4, flood damage in *High-risk* municipalities receives zero weight. The corresponding bank-prefecture-level measure is defined as:

$$LandPriceDamage_{i,p,t} = - \sum_{m \in p} 1(m \in Low) \times \hat{\gamma}_L \log\left(\frac{damage_{m,t-1}}{pop_{m,t-1}}\right) \times \frac{loan_{i,m,t}}{loan_{i,p,t}} \quad (10)$$

We then estimate the following specifications:

$$y_{i,t} = \beta_2 LandPriceDamage_{i,t-1} + \beta_1 Exposure_{i,t-1} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (11)$$

$$y_{i,p,t} = \beta_2 LandPriceDamage_{i,p,t-1} + \beta_1 Exposure_{i,p,t-1} + \delta_{i,t} + \eta_{p,t} + \xi_{p,i} + \varepsilon_{i,p,t} \quad (12)$$

If the collateral channel is present, we anticipate that β_2 will be positive for credit cost ratios and negative for ROA with statistical significance, as banks with greater exposure to flood-induced land price declines are expected to experience more pronounced depreciations in collateral value, leading to an increase in credit cost and a subsequent decline in profitability. Regarding credit supply, we expect β_2 to be negative as the collateral channel theoretically tightens borrowing constraints and suppresses lending activity.

However, our variable $LandPriceDamage$ might not exclusively capture the collateral channel. Specifically, because it also reflects a bank's exposure to regions with limited historical flood experience, the coefficient β_2 could remain statistically significant if firm performance is sensitive to such exposure, even when the collateral channel is not the primary driver. For instance, [Yamamoto and Naka \(2022\)](#) find that adverse firm-level outcomes are more pronounced in

¹² The correlation coefficient between the explanatory variables $LandPriceDamage$ and $Exposure$ is 0.26. By accounting for regional heterogeneity in the elasticity of land prices to flood damage, we mitigate potential concerns regarding multicollinearity.

municipalities with less frequent exposure to flooding in the past.¹³ In this case, the coefficient β_2 may also capture heterogeneity in firms' responses to flood damage. To address this potential confounding factor and isolate the collateral mechanism from other channels, we interact *LandPriceDamage* with the bank's reliance on real estate collateral. Specifically, we estimate the following specifications:

$$y_{i,t} = \beta_4 \text{LandPriceDamage}_{i,t-1} \times \text{RECollateralRatio}_{i,t-1} + \beta_3 \text{LandPriceDamage}_{i,t-1} + \beta_2 \text{Exposure}_{i,t-1} + \beta_1 \text{RECollateralRatio}_{i,t-1} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (13)$$

$$y_{i,p,t} = \beta_4 \text{LandPriceDamage}_{i,p,t-1} \times \text{RECollateralRatio}_{i,t-1} + \beta_3 \text{LandPriceDamage}_{i,p,t-1} + \beta_2 \text{Exposure}_{i,p,t-1} + \delta_{i,t} + \eta_{p,t} + \xi_{p,i} + \varepsilon_{i,p,t} \quad (14)$$

where $\text{RECollateralRatio}_{i,t-1}$ represents bank i 's share of loans secured by real estate in year $t - 1$.^{14,15} The primary coefficient of interest is β_4 . If the collateral channel is present, we expect β_4 to be statistically significant and of a sign consistent with a deterioration in financial conditions and a reduction in lending as banks with greater reliance on real estate collateral should be more sensitive to a decline in collateral value. Given that the impact of floods on banks via firm performance should be independent of a bank's specific reliance on real estate collateral, this approach allows us to disentangle the collateral channel from alternative transmission mechanisms.

5.2 Results

Table 5 presents the results for Eq.(11) and (12). The coefficient β_2 is statistically significant at the 10% level with the expected signs for credit cost ratios and ROA, although their economic significance is minor. In contrast, β_2 lacks statistical significance regarding credit supply, indicating that land-price shocks do not, on average, lead banks to tighten borrowing constraints for their clients.

¹³ The relationship between past flood experience and the magnitude of flood impacts on firms remains relatively understudied, and the existing evidence is mixed. For example, in contrast to [Yamamoto and Naka \(2022\)](#), [Noth and Rehbein \(2019\)](#) report that the impact of the 2013 Elbe River flood did not differ significantly between firms with and without exposure to a prior severe flooding event in 2002.

¹⁴ We do not include the explanatory variable $\text{RECollateralRatio}_{i,t-1}$ in Eq.(14) since the equation already has the bank-year fixed effect.

¹⁵ A concern may arise regarding endogenous portfolio shifts over time; for instance, banks may increase collateral requirements as borrowers' credit quality deteriorates, leading to reverse causality. To mitigate this potential endogeneity problem, we instrument the interaction terms using the initial real estate collateral ratio from 2001 and its interaction with *LandPriceDamage*. The first-stage F-statistics significantly exceed the conventional threshold of 10, confirming the relevance of our instruments.

Table 5. Impacts of land price damage on banks

Variables	Bank level			Bank-prefecture level
	NPL ratio	Credit cost ratio	ROA	log(Loans)
	(1)	(2)	(3)	(4)
LandPriceDamage (t-1)	0.05 *	0.01 *	-0.01 *	0.00
	(0.03)	(0.01)	(0.00)	(0.01)
Exposure (t-1)	0.04	0.01	-0.01	0.09 ***
	(0.03)	(0.01)	(0.00)	(0.01)
Obs.	5556	5556	5556	8614
Within R-sq	0.002	0.002	0.001	0.023
Bank FE	Y	Y	Y	N
Year FE	Y	Y	Y	N
Bank-Year FE	N	N	N	Y
Bank-Pref FE	N	N	N	Y
Pref-Year FE	N	N	N	Y

Note: The table reports regression results for Eq.(11) and Eq.(12). Dependent variable is indicated at the top of each column. The sample period is FY2001-FY2023. The independent variables are standardized to have standard deviation of one. Standard errors clustered at the bank level (or bank-prefecture-level for log(Loans)) are presented in parentheses. The ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

Table 6 displays the estimates for Eq.(13) and (14). The interaction term β_4 is statistically significant for both credit cost ratios and credit supply. These results indicate that the adverse effects of floods on credit costs are amplified and credit expansions are suppressed for banks with a higher reliance on real estate collateral. This evidence is consistent with the operation of the collateral channel. Regarding credit costs, while a bank with the sample-mean real estate collateral ratio (30%) exhibits a marginal 0.02% increase in its credit cost ratio in response to a one-standard-deviation flood-induced decline in land prices, a bank at the upper bound of our sample (86%) experiences a 0.09% rise, which is a fivefold amplification in sensitivity to the same shock. Regarding credit supply, the results imply that a flood-induced decline in land prices may reduce a bank's credit supply particularly when its real estate collateral ratio significantly exceeds the sample mean. For instance, while a bank with the sample-mean real estate collateral ratio (30%) shows no significant tightening of credit, a bank at the upper bound of our sample (86%) reduces credit supply by approximately 10% in response to a one-standard-deviation shock to land prices. Notably, even while accounting for these factors, the overall flood exposure ($Exposure_{i,p,t-1}$) remains positively associated with credit supply. These findings suggest that while banks expand lending in response to flood-related demand, the decline in collateral values generates a countervailing pressure.

Table 6. Impacts of land price damage conditional on real estate collateral ratios

Variables	Bank level			Bank-prefecture level
	NPL ratio	Credit cost ratio	ROA	log(Loans)
	(1)	(2)	(3)	(4)
LandPriceDamage (t-1)	0.005	0.001 *	0.000	-0.002 **
x RE Collateral Ratio (t-1)	(0.003)	(0.001)	(0.000)	(0.001)
LandPriceDamage (t-1)	-0.066	-0.019	-0.012	0.034 **
	(0.091)	(0.019)	(0.012)	(0.017)
RE Collateral Ratio (t-1)	0.049 ***	0.007 ***	-0.003	
	(0.012)	(0.001)	(0.001)	
Exposure (t-1)	0.049 *	0.008	-0.006	0.090 ***
	(0.028)	(0.006)	(0.004)	(0.013)
Obs.	5523	5523	5523	8557
Within R-sq	0.04	0.01	0.01	0.02
Bank FE	Y	Y	Y	N
Year FE	Y	Y	Y	N
Bank-Year FE	N	N	N	Y
Bank-Pref FE	N	N	N	Y
Pref-Year FE	N	N	N	Y

Note: The table reports regression results for Eq.(13) and Eq.(14). Dependent variable is indicated at the top of each column. The sample period is FY2001-FY2023. The independent variables are standardized to have standard deviation of one. The interaction term is instrumented on the real estate collateral ratio of each bank at the beginning of the sample period and its interaction with *LandPriceDamage*. Standard errors clustered at the bank level (or bank-prefecture-level for log(Loan)) are presented in parentheses. The ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

6. Conclusion

This paper examines how flood disasters affect banks' financial conditions, with particular emphasis on the collateral channel operating through changes in land prices. Using municipality-level flood damage data matched with bank balance sheet information and branch locations in Japan, we document two main findings.

First, exposure to floods adversely affects banks' financial conditions, as evidenced by higher NPL ratios, higher credit cost ratios, and lower returns on assets. These effects are statistically significant but economically minor, suggesting that while flood shocks could weaken bank balance sheets, they have not—at least based on historical events—posed material risks to banks' financial conditions.¹⁶ Simultaneously, we find that affected banks expand credit supply at the

¹⁶ Note that the estimated effects do not disentangle the impacts of government expenditures in affected areas following flood events. It is also important to note that climate change could lead to a non-linear escalation of these risks in the future as extreme weather events become more frequent and severe.

bank–prefecture level following these events. This expansion may reflect heightened post-disaster credit demand driven by reconstruction and liquidity needs.

Second, banks exhibit heterogeneous responses to floods in a manner consistent with the collateral channel. Specifically, banks with greater exposure to areas where land prices decline sharply following a flood experience more pronounced deteriorations in financial performance and a relative slowdown in credit expansion. Moreover, these effects are amplified for banks with higher shares of loans with real estate collateral. This pattern cannot be explained solely by a deterioration in borrowers' ability to repay their debts and thus points to the presence of the collateral channel.

Our findings contribute to the growing literature on climate-related financial risks by highlighting a potential role of asset price sensitivity, rather than disaster exposure alone, in shaping banks' responses to natural hazards. From a policy perspective, the results suggest that climate risk assessments should incorporate dynamics of collateral values and banks' degree of reliance on real estate collateral, in addition to geographic exposure measures. While this study relies on bank-level and municipality-level data due to data limitations, incorporating firm-level information such as financial statements and exposure to specific flood events remains a task for future research. If such granular data can be matched with bank-side data, it would allow for an even sharper identification of how flood-induced shocks propagate to banks' balance sheets. As climate change increases the frequency and severity of flood events, understanding these transmission mechanisms will be essential for evaluating the resilience of financial intermediation.

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Appendix

A. Additional Specifications with Multiple Lags of Flood Exposure

This appendix examines the sensitivity of the baseline results to the inclusion of multiple lags of flood exposure. While the main specifications include a single lag of flood exposure, consistent with the literature documenting predominantly short-lived disaster effects, it is possible that flood impacts persist beyond one year.

To assess this possibility, we re-estimate the baseline regressions by including up to three annual lags of the flood exposure variables. The results indicate that the coefficients on the first-lag flood exposure variables remain similar in magnitude and statistical significance to those reported in the main tables. In contrast, coefficients on longer lags are generally smaller and become statistically insignificant after two years across specifications.

Table A1. Inclusion of multiple lags in the baseline model

Variables	Bank level			Bank-prefecture level
	NPL ratio (1)	Credit cost ratio (2)	ROA (3)	log(Loans) (4)
Exposure (t-1)	0.07 ** (0.03)	0.01 * (0.01)	-0.01 ** (0.00)	0.08 *** (0.01)
Exposure (t-2)	0.07 *** (0.03)	0.01 ** (0.01)	-0.01 *** (0.00)	0.08 *** (0.01)
Exposure (t-3)	0.05 * (0.03)	0.00 (0.01)	0.00 (0.00)	0.06 *** (0.01)
Obs.	4268	4268	4268	5668
Within R-sq	0.004	0.002	0.004	0.056
Bank FE	Y	Y	Y	N
Year FE	Y	Y	Y	N
Bank-Year FE	N	N	N	Y
Bank-Pref FE	N	N	N	Y
Pref-Year FE	N	N	N	Y

Note: Dependent variable is indicated at the top of each column. The sample period is FY2001-FY2023. The independent variables are standardized to have standard deviation of one. Standard errors clustered at the bank level (or bank-prefecture-level for log(Loans)) are presented in parentheses. The ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

These findings suggest that the effects of floods on banks' financial conditions materialize primarily within one year. Consequently, the choice to focus on a single lag in the baseline analysis does not affect the qualitative conclusions.

B. Heterogeneity by Bank Type: Mega/Regional Banks versus *Shinkin* Banks

This appendix investigates whether the estimated effects differ across bank types by splitting the sample into mega/regional banks and *shinkin* banks. These two groups differ in size, geographic scope, and client composition, which may influence their exposure to flood risk and their response to disaster shocks (Blickle et al., 2021; Petkov, 2022). Table B1 presents the descriptive statistics for the two groups of banks. *Shinkin* banks are generally smaller and tend to rely more on real estate as loan collateral compared to mega and regional banks.¹⁷ Therefore, the analysis of this paper implies that *shinkin* banks should be more susceptible to flood damage through the collateral channel.

Table B1. Descriptive Statistics by Bank Type

Variable	Mega and regional banks		<i>Shinkin</i> banks	
	Obs.	Mean	Obs.	Mean
Loans (bil. yen)	2059	4569	4646	265
NPL ratio (%)	2059	0.4	4646	0.4
Credit cost ratio (%)	2059	0.3	4646	0.3
ROA (%)	2059	0.1	4646	0.1
Real estate collateral ratio (%)	2059	22.6	4646	33.0
Share of branches hit by floods (%)	2059	37.4	4646	36.4

Note: The table reports descriptive statistics for the sample between FY2001 and FY2023.

We re-estimate the baseline regressions separately for mega/regional banks and *shinkin* banks using identical specifications. Tables B2 and B3 report the estimation results for the regressions corresponding to Table 2 and Table 3 in the main analysis, respectively. They show that the qualitative patterns documented in the full sample remain robust across both subsamples: namely, flood exposure is associated with higher credit risk and lower profitability, while increasing credit supply. Quantitatively, the impacts on credit risk measures and profitability tend to be larger and more statistically significant, while the effect on credit supply is smaller for *shinkin* banks. This is consistent with their higher reliance on real estate collateral within limited geographic areas. Overall, the impact of floods on financial conditions remains economically limited across different types of banks.

¹⁷ In terms of geographic scope, *shinkin* banks operate within much narrower, strictly defined regions compared to mega and regional banks. Their client composition is also legally restricted: they function as cooperatives that primarily lend to local residents and small-scale firms (typically those with fewer than 300 employees or limited capital) who are members of the cooperative.

Table B2. Estimation results with dummy explanatory variables

Variables	Bank level			Bank-prefecture level
	NPL ratio (1)	Credit cost ratio (2)	ROA (3)	log(Loans) (4)
Panel A: Mega and regional banks				
Severe floods defined as > 90th percentile				
flood(t-1)	0.24 *** (0.08)	0.03 (0.02)	0.00 (0.02)	0.02 * (0.01)
Within R-sq	0.00386	0.00086	0.00002	0.00044
Severe floods defined as > 95th percentile				
flood(t-1)	0.09 (0.06)	0.01 (0.02)	-0.01 (0.02)	0.01 (0.01)
Within R-sq	0.00101	0.00007	0.00013	0.00003
Obs.	2057	2057	2057	13207
Panel B: <i>Shinkin</i> banks				
Severe floods defined as > 90th percentile				
flood(t-1)	0.12 * (0.06)	0.02 * (0.01)	-0.02 ** (0.01)	0.00 (0.00)
Within R-sq	0.00093	0.00064	0.00113	0.00001
Severe floods defined as > 95th percentile				
flood(t-1)	0.01 (0.08)	0.03 (0.02)	-0.03 *** (0.01)	-0.01 (0.01)
Within R-sq	0.00001	0.00052	0.00158	0.00062
Obs.	4646	4646	4646	4646
Bank FE	Y	Y	Y	N
Year FE	Y	Y	Y	N
Bank-Year FE	N	N	N	Y/N
Bank-Pref FE	N	N	N	Y
Pref-Year FE	N	N	N	Y

Note: Dependent variable is indicated at the top of each column. The sample period is FY2001-FY2023. Standard errors clustered at the bank level (or bank-prefecture-level for log(Loans)) are presented in parentheses. The ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels. We include bank-year fixed effects only for mega and regional banks since most *shinkin* banks operate in single prefectures and hence including bank-year fixed effects for these banks would absorb a significant amount of variations in the dependent variable.

Table B3. Estimation results with continuous explanatory variables

Variables	Bank level			Bank-prefecture level
	NPL ratio	Credit cost ratio	ROA	log(Loans)
	(1)	(2)	(3)	(4)
Panel A: Mega and regional banks				
Exposure (t-1)	0.05 (0.04)	0.01 (0.01)	-0.01 (0.01)	0.09 *** (0.01)
Obs.	2045	2045	2045	8614
Within R-sq	0.0009	0.0008	0.0004	0.0232
Panel B: <i>Shinkin</i> banks				
Exposure (t-1)	0.07 ** (0.03)	0.01 ** (0.01)	-0.01 ** (0.00)	0.00 (0.00)
Obs.	3511	3511	3511	3511
Within R-sq	0.0015	0.0010	0.0012	0.0006
Bank FE	Y	Y	Y	N
Year FE	Y	Y	Y	N
Bank-Year FE	N	N	N	Y/N
Bank-Pref FE	N	N	N	Y
Pref-Year FE	N	N	N	Y

Note: Dependent variable is indicated at the top of each column. The sample period is FY2001-FY2023. Standard errors clustered at the bank level (or bank-prefecture-level for log(Loans)) are presented in parentheses. The ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels. We include bank-year fixed effects only for mega and regional banks since most *shinkin* banks operate in single prefectures and hence including bank-year fixed effects for these banks would absorb a significant amount of variation in the dependent variable.