THE ROLE OF DOMINANT BANKS IN THE MARKET: HOW DOES LENDING CHANGE DURING ECONOMIC DISTRESS?

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Abstract: This study examines how banks in Mongolia adjust their lending behavior during periods of industry-level financial distress. Specifically, it explores whether banks with dominant exposure to a distressed sectors absorb shocks by maintaining or increasing credit supply, or whether they amplify distress through reduced lending. Using a detailed bank-industry-time panel dataset from the Bank of Mongolia, covering 12 banks and 17 economic sectors from 2017 to 2024, and employing fixed-effects models, the study finds that banks' lending responses to distress are shaped by their market share, exposure to the industry, industry's financial health, and supply chain linkages. In particular, large or highly exposed banks tend to sustain lending to preserve sectoral stability, while industries with high financial efficiency and upstream supply roles receive relatively more credit. These findings highlight the stabilizing role of credit concentration in emerging markets and provide policy-relevant insights into how large banks influence the transmission of financial shocks through credit channel.

Keywords: *Bank lending channel, Credit transmission, Industry distress, Bank-industry relationship, Mongolia*

Jel Code: *E44, E51, G21*

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I. Introduction

The economic disruptions triggered by the COVID-19 pandemic have renewed global interest in understanding contagion effects and the interconnectedness within and across economies. The pandemic exposed vulnerabilities in supply chains and financial systems, highlighting how sectoral shocks can transmit through both real and financial linkages (Utz, Feyen, Ahued, Nie, & Moon, 2020). In particular, the banking sector plays a central role in this propagation process, serving as both a stabilizer and a transmission channel of financial shocks (Demirgüç-Kunt, Pedraza, & Ruiz-Ortega, 2021) (Dicanio & Montesi, 2021).

A well-functioning credit channel underpins financial stability and supports economic growth by facilitating liquidity and investment (Oliner & Rudebusch, 1995). However, when industries experience distress, banks' responses—whether to cut, maintain, or expand lending—determine the extent of shock amplification in the real economy. Understanding the factors shaping these responses is therefore crucial for designing effective macroprudential and monetary policies (Chi, 2009).

Financial linkage between the banking sector and industry through the credit channel represents two sides of the same coin. On one side, it underpins financial stability within the economy; on the other, it serves as a catalyst for economic growth by facilitating private investment through bank lending. Understanding how banks respond to economic shocks and how their structural characteristics—such as market share and credit exposure—influence lending decisions is crucial for effective policy design. The majority of studies examining this channel emphasize the banking sector's lending behavior, particularly its propensity to extend credit when the associated firm is experiencing financial distress. The incentive underlying this relationship, from the banks' perspective, is to mitigate potential losses that may arise from the financial distress of the firms to which they are exposed. Dahiya, et al., (2003) provide empirical evidence that banks with prior lending relationships to distressed firms suffer greater shareholder wealth losses, underscoring the financial risk of firm default. Similar findings by Bruhnner & Krahnen (2008), Rosenfeld (2014) and Daniel (2016) reinforce the idea that banks seek to preserve lending relationships to safeguard their own balance sheets.

The literature also highlights how banks proactively adjust loan terms in anticipation of distress. For example Donker, et al., (2018) show that banks modify lending requirements—such as interest rates, collateral demands, and loan maturities—after firms issue profit warnings. Interestingly, these precautionary measures are associated with improved borrower outcomes, including reduced default risk and increased profitability. The structure of lending syndicates plays a role as well. Lee & Mullineaux (2004) examine syndicated loan composition and find that syndicates are often organized to enhance monitoring and facilitate renegotiation in the event of borrower distress. This demonstrates that lending arrangements are designed not only to share risk but also to manage it effectively.

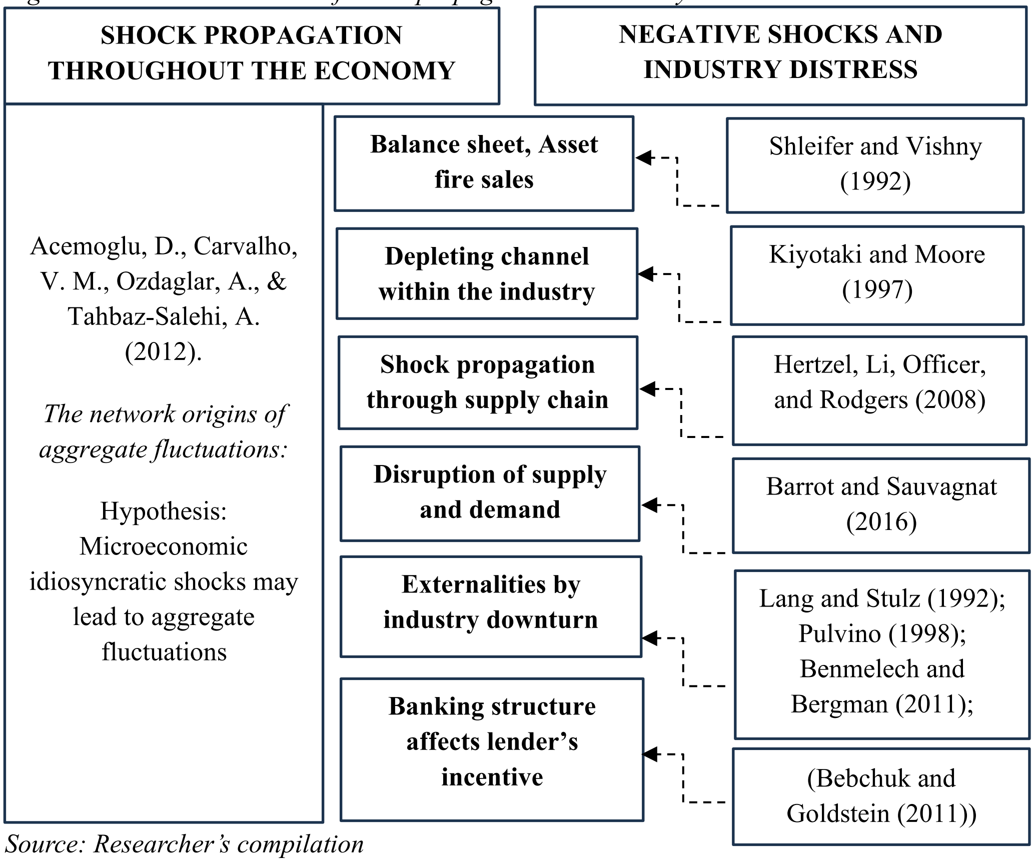
The reciprocal influence—firms' behavior in maintaining stable banking relationships—is another important aspect of this linkage. Ongena, et al., (2003) use an event study approach to analyze the effects of bank distress announcements on client firms' stock prices. They find that firms with existing relationships to distressed banks experience only minor and temporary market reactions, suggesting that firms value stable bank ties and that the market views these relationships as resilient. The lending relationship also serves as a conduit for transmitting financial shocks to the broader economy. Carvalho et al. (2015) provide empirical evidence supporting this transmission mechanism, highlighting that the deterioration in the value of lending relationships constitutes a key channel through which bank distress exerts adverse effects on the real economy.

Our research contributes to two key strands of this literature (Figure 1): The first explores the propagation of idiosyncratic shocks and their macroeconomic implications. Pioneered by Acemoglu et al. (2012), this line of work argues that micro-level disruptions—such as those in lending relationships—can generate aggregate economic fluctuations. The second strand focuses on the effects of industry-level distress, including balance sheet deterioration, asset fire sales, supply chain disruptions, and demand collapse (see Barrot & Julien (2016), Kiyotaki & John (1997), Carvalho, et al., (2015), Hertzel (2008), Shleifer & Robert (1992)).

Within this broader context, relatively few studies address how bank-specific characteristics, particularly market share, influence lending behavior during firm-level or industry-level distress. Bebchuk and Goldstein (2011), as well as Mariassunta and Farzad (2018), argue that banks with significant market share are more likely to internalize the externalities associated with firm or industry distress. Such banks have a stronger incentive to continue lending to maintain sectoral stability, thus containing the potential for broader systemic contagion.

We find Mongolia is the suitable example to work with and to contribute in a way of above mentioned 2 pillars of the literature as the commercial banks have played a central role in maintaining credit flows to industries—whether sourced from government programs, central bank interventions, or their own balance sheets. This role is particularly critical given the high concentration of the banking sector, where the four largest banks account for over 80% of total system assets, loans, and deposits. Prior literatures in the context of Mongolia, are more macro-focused. For example, Enkhzaya (2011, 2018) investigates the heterogeneity in banks' responses to monetary policy and macroeconomic shocks. Her findings suggest that smaller banks with lower liquidity and capital adequacy ratios are more vulnerable to policy-induced credit fluctuations. Munkhbayar (2018) examines the impact of non-performing loans on credit supply, finding that a rise in NPLs significantly dampens lending activity, revealing a strong negative feedback loop between asset quality and credit availability.

Figure 1. Relative literatures of shock propagation and industry distress



Source: Researcher's compilation

Thus, this study examines the bank lending channel in Mongolia through the lens of bank-industry interactions, with a focus on how banks adjust their lending behavior in response to industry-level financial distress. The findings aim to inform macroprudential and monetary policy by highlighting the incentives of large banks and the potential transmission mechanisms of credit shocks. As the Bank of Mongolia operates under a mandate to ensure financial stability, and given the dominance of banks in the financial sector, a deeper understanding of the credit channel and its systemic risks is essential. By incorporating both bank-level and industry-level data, this study offers a novel perspective on the interdependencies between the banking sector and the real economy in Mongolia. It provides valuable insights for strengthening macroprudential oversight and tailoring policy responses to the unique structure of the Mongolian financial system.

Accordingly, our study examines how banks adjust lending across industries in response to financial distress, and how market share influences these adjustments. Specifically, we ask three research questions:

Do banks with larger market shares sustain lending to industries facing financial distress?

How do industry financial characteristics—such as solvency and efficiency—affect banks' responses?

To what extent do supply-chain linkages amplify or mitigate these credit responses across industries?

Our empirical analysis contributes to the literature in three ways. First, it provides novel evidence on the interaction between credit concentration and industry distress in an emerging market context. Second, by combining bank-level and industry-level datasets, it allows for a granular view of the credit channel, distinguishing between shocks in borrower industries and lending responses by banks. Third, it explores the supply-chain dimension of shock propagation, offering insights into how banks internalize externalities not only within directly affected industries but also among their supplier and customer sectors.

The findings indicate that banks with higher market shares are more likely to maintain or increase lending during periods of industry-level distress, suggesting that concentration can have stabilizing effects under certain conditions. However, the extent of this response depends on the financial health and efficiency of industries. Moreover, the results show that banks are more likely to sustain credit to distressed industries that serve as key suppliers, highlighting the upstream role of production networks in mitigating systemic risk.

The remainder of the paper is structured as follows. Section 2 describes the construction of variables and data descriptives. Section 3 outlines the empirical methodology. Section 4 and 5 present the main findings and concluding remarks respectively.

II. Data

Our analysis is based on two datasets: a **bank-industry-time level dataset** and an **industry-time level dataset**. The bank-industry-time level captures loan-level interactions between all 12 currently operating banks and 17 industries[3] in Mongolia, covering the period from 2017 to 2024 (in both monthly and quarterly frequency). This dataset's initial source are banks and it is compiled internally by the Research and Statistics Department of the Bank of Mongolia.

The core lending variables used in our analysis—serving as dependent variables—are:

1. **Newly issued loans**, the volume of new loans extended by bank i to industry j at time t;
2. **Loan outstanding**, the stock of loans from bank i to industry j at time t;

We use loan supply variables as our dependent variables because they directly capture banks' lending behavior in response to changes in industry conditions, allowing us to assess whether and how banks adjust credit provision when their borrowing sectors experience financial distress. By examining both the flow (new issuance) and stock (outstanding loans) of credit, we aim to provide a comprehensive view of how banks respond in both the short term and over time.

[3] *Due to data limitations, 4 smaller sectors were aggregated into broader industry groups, thus resulting in 17 industries compared to standard 21 industry classification.*

To account for differences in banks' exposure and incentives to specific industries during periods of industry-level distress, we also include each **bank’s market share** in a given industry at each point in time. This is calculated as the share of a bank’s loan exposure in an industry relative to the total loans extended to that industry by all banks. The underlying idea is that banks with a larger share of loan exposure in a given industry are more vulnerable to adverse developments in that sector. These high-market-share lenders face greater potential losses and thus have stronger incentives to prevent fire sales or downward price spirals that may occur during downturns. So we calculate the bank i’s market share in industry j at time t as bank i’s outstanding loans to industry j at time t divided by total outstanding loans to industry j at time t across all banks. This measure captures each bank’s relative financial stake in a particular industry at a given point in time and serves as a proxy for the strength of its incentives to support the industry during downturns.

To assess industry-level financial distress, we construct a binary **distress indicator** for each industry using the NPL ratio (non-performing loans to total loan outstandings). The rationale is that an abnormally high NPL ratio suggests widespread repayment difficulties, indicating distress at the industry level. An industry j at time t is identified as distressed if its non-performing loan (NPL) ratio exceeds one standard deviation above the median NPL ratio across all industries:

$$\mathrm{Distress}_{jt} = \begin{cases} 1 \text{ if NPL ratio}_{jt} > \text{median}(\text{NPL ratio}_j) + 1\text{std}(\text{NPL ratio}_j) \\ 0, \text{otherwise} \end{cases}$$

In addition, to capture structural characteristics and financial health of industries, we calculate industry-level financial ratios from the Ministry of Finance’s electronic tax database for the years 2017 to 2022. These include the **asset liabilities ratio**, which reflects solvency risk, and the **asset turnover ratio**, which captures operational efficiency. Since the industry efficiency ratios are not available for 2023–2024, the industry efficiency specifications are estimated only for the years with available data. Also, we calculated supplier shares and customer shares for each industry from annual Input-Output tables of National Accounts reported by the National Statistical Office of Mongolia. (See Appendix 1 for detailed variable definitions and data sources.)

Table 1. Descriptive Statistics

	units	Mean	Median	SD	Min	Max	N monthly	N quarterly
Bank-industry-time level data								
Newly issued loans	bln MNT	12.5	0.1	472.4	0	695	17952	5984
Loan outstanding	bln MNT	100.2	7.9	297.3	0	4410	17952	5984
Ln(newly issued)	-	7.3	7.4	2.67	-9	13.45	17952	5984
Ln(outstanding)	-	9.1	9.4	3.97	-70	15.3	17952	5984
YoY of new loans	percent	25.2	23.9	173	-1428	1499	7849	3294
YoY of outstanding	percent	12.5	6.4	188	-3940	4043	13020	3294
Market share	percent	9.1	2.71	14.4	0	95	17952	5984

Industry-time level data								
NPL_ratio	percent	14.0	8.9	14.4	0.2	77.4	17952	5984
Distress dummy	-	0.19	0	0.39	0	1	17952	5984
Asset liabilities ratio	percent	1.53	1.26	0.93	0.56	7.36	13464	4488
Asset turnover ratio	percent	0.45	0.5	0.24	0.04	1.05	13464	4488
Supplier share	percent	0.82	0.83	0.16	0.32	1.0	16896	5632
Customer share	percent	0.83	0.88	0.17	0.32	1.0	16896	5632

Note: *The monthly panel consists of 17,952 observations covering 96 time periods (2017m1–2024m12) for 11 banks across 17 industries. The quarterly panel includes 5,984 observations over 32 time periods (2017q1–2024q4) for the same set of banks and industries.*
Source: Bank of Mongolia, NSO, MoF, Researchers' computation

As shown in Table 1, the loan supply variables display considerable variation across bank-industry-time observations. The average volume of **newly issued loans** across industries is 12.5 billion MNT, with a high standard deviation of 472.4 billion MNT, reflecting significant heterogeneity across industries and banks. The log-transformed values help reduce skewness, with the mean of log new loans at 7.3. Similarly, the average **loan outstanding** is 100 billion MNT, with a wide range—from zero to 4.4 trillion MNT—indicating differing levels of exposure. The year-on-year growth rates of both new loans and loan outstanding exhibit large dispersions, suggesting strong dynamics in bank lending behavior over time.

Turning to **market share**, the average share of a bank's outstanding loans in a given industry is 9.1%, but the distribution is highly skewed, with a median of just 2.7% and a maximum of 95%. This suggests that while most banks hold small shares in many sectors, a few dominate certain industries. Highly concentrated industries include water supply, agriculture, professional services, communication, and administrative services. In terms of bank size, large banks consistently dominate loan markets across all industries, especially in sectors like education, public service, and finance. Medium-sized banks hold moderate shares, with more noticeable presence in trade, construction, and manufacturing. Small banks contribute minimally overall, with slightly higher activity in agriculture and mining, indicating a more specialized role (see Appendix 6).

The standard deviation of the NPL ratio across industries is 14.4%, with substantial variation depending on the sector and time period. Overall, we find that industries experienced **financial distress** in 19% of all observations, a reasonable outcome given that our sample period includes the COVID-19 pandemic. Industries that experienced prolonged or repeated distress include manufacturing, water supply, professional services, administrative, and public services, each showing multiple or extended periods of elevated NPLs, especially during the COVID-19 pandemic. In contrast, industries like communication, transportation, and trade had relatively low and stable NPL ratios with minimal or no distress periods (see Appendix 7).

We compared average loan issuance during distress and non-distress periods (See Appendix 8). During non-distress periods, large banks dominate lending activity, particularly in trade, finance, and the "other" sectors, with significant issuance also observed from medium-sized banks in communication and finance. However, during distress periods, lending volumes contract substantially across all bank sizes and sectors, with noticeable reductions even in previously active sectors. While large banks still maintain relatively higher issuance levels, especially in trade and the "other" category, the overall decline illustrates a more cautious lending stance during industry downturns.

III. Methodology

This study aims to examine whether banks with a larger market share in a particular industry are more likely to internalize the negative externalities associated with industry-level distress. Specifically, we investigate whether such banks are more inclined to continue lending to distressed industries, thereby mitigating the amplification of adverse shocks.

Our empirical strategy builds on the identification approaches used in prior work, particularly by Mariassunta and Farzad (2018), who applied a linear regression framework to assess banks’ lending behavior toward distressed firms. Their findings provided novel evidence that a concentrated credit system may contribute positively to financial stability by incentivizing banks to internalize the spillover costs of financial distress.

In our analysis, we used a high-dimensional fixed effects (FE) panel regression estimation. We recognize that banks' lending decisions are influenced not only by industry-specific factors but also by macroeconomic conditions such as changes in monetary policy. To control for these external influences, we include fixed effects that absorb time-varying unobserved heterogeneity at both the industry and bank levels.

Our baseline regression model is specified as follows for monthly frequency version:

$$y_{ijt} = \beta_1 \text{Market share}_{ij,t-6} \times \text{Distress}_{j,t-3} + \beta_2 \text{Market share}_{ij,t-6} + \theta_{jt} + \varphi_{it} + \varepsilon_{ijt} \tag{1}$$

where

- $y_{ijt} = \begin{cases} \ln \text{nloan}_{\text{ijt}} - \log(\text{newly issued loans}_{\text{ijt}}) \text{ or} \\ \text{New loans issued at time t from bank i to industry j} \\ \ln \text{loan}_{\text{ijt}} - \log(\text{loan outstanding}_{\text{ijt}}) \text{ or} \\ \text{Loan outstanding of bank i to industry j at time t} \end{cases}$
- $\text{Distress}_{j,t-1}$ is an indicator variable for whether industry j is in distress in period $t-1$;
- $\text{Market share}_{i,j,t-2}$ bank i’s share in total loan outstanding in industry j at time $t-2$;
- θ_{jt} and φ_{it} denote industry-period and bank-period fixed effects, respectively. In particular, and θ_{jt} captures all time-varying unobserved heterogeneity at the industry level; φ_{it} captures all time-varying unobserved heterogeneity across banks.

To address our second research question—whether the effect of market share on lending behavior in distress varies with industry characteristics—we extend the model following the approach of Giannetti and Saidi (2018). The industry efficiency specification of the model is as follows:

$$\begin{aligned} y_{ijt} = {} & \beta_1 \text{Market share}_{ij,t-6} \times \text{Distress}_{j,t-3} \\ & + \beta_2 \text{Market share}_{ij,t-6} \times \text{Characteristics}_{j,t-3} \\ & + \beta_3 \text{Market share}_{ij,t-6} \times \text{Distress}_{j,t-3} \times \text{Characteristics}_{j,t-3} \\ & + \theta_{jt} + \varphi_{it} + \varepsilon_{ijt} \end{aligned} \tag{2}$$

where $\text{Characteristics}_{j,t-1}$ captures industry efficiency ratios measured prior to distress. Specifically, we use the **asset liabilities ratio** as a proxy for industry solvency and the **asset turnover ratio** as a measure of operational efficiency. These variables reflect how easily industries can withstand and respond to financial shocks, thus influencing the potential externalities associated with distress. This specification allows us to test whether banks with higher market shares are particularly responsive to distress in industries where the externalities of failure are more severe.

The choice of lags in the interaction terms follows both theoretical reasoning and empirical considerations. Specifically, we use the 6-month lag for the market share variable (t–6) to account for the time it takes for banks' existing exposure and portfolio composition to influence subsequent lending decisions. Similarly, the 3-month lag for the distress indicator (t–3) reflects the delay between the onset of financial stress in an industry and its observable impact on credit allocation, as banks typically respond to deteriorating borrower conditions with some lag due to monitoring and internal risk assessment processes. These lag lengths were also selected after testing several alternative specifications (e.g., t–3, t–6, and t–12), and the results were found to be most robust and economically meaningful for the t–6 and t–3 structure.

To capture the amplification of credit shocks through supply chains, we augment our baseline model by interacting the market share–distress term with industry-level supplier and customer shares. This triple interaction allows us to examine whether banks internalize potential spillover risks by adjusting lending not only to distressed industries but also to those linked via input-output relationships.

The supply chain effect specification of the model is as follows:

$$\begin{aligned} y_{ijt} = {} & \beta_1 \text{Market share}_{ij,t-6} \times \text{Distress}_{j,t-3} + \beta_2 \text{Market share}_{ij,t-6} \\ & + \beta_3 \text{Market share}_{ij,t-6} \times \text{Distress}_{j,t-3} \\ & \times \mathit{Supplier/Customer}\ \text{share}_{j,t-3} \quad + \theta_{jt} + \varphi_{it} + \varepsilon_{ijt} \end{aligned} \tag{3}$$

where $\text{Supplier share}_{j,t-1}$ is defined as the proportion of inputs that industry j sources from other industries, weighted by each input industry's share in the total input supply to j, while the $\text{Customer share}_{j,t-1}$ is defined as the proportion of outputs that industry j supplies to other industries, weighted by each receiving industry's share in total demand for j's output.

IV. Results

4.1 Baseline specifications

Our baseline specifications aim to investigate whether high market share triggers the bank to issue more loan when the sector is in distress using monthly 3 dimensional (bank-industry-time) panel dataset. The dependent variable is logarithm of new loan issuance of bank j to industry i during time t. As an alternative proxy for loan supply, we also use the logarithm of loan outstanding within the same panel structure. We considered both monthly and quarterly frequency to check the consistency of the estimated coefficients.The main explanatory variables of interest are market share and industry distress, as defined in the Data section.

As in the work of (Mariassunta & Farzad, 2018), we expect banks with high market shares in a given industryin the past have stronger incentives to continue lending—particularly during periods of industry distress—because they are more exposed to potential losses and have a greater stake in stabilizing the sector. To reflect this mechanism, we use a **6-month lag** for the market share variable, assuming that banks make lending decisions based on prior exposure rather than contemporaneous loan shares. Similarly, we apply a **3-month lag** to the distress variable to reflect the idea that it takes time for banks to assess deteriorating conditions in a sector and adjust their lending behavior accordingly. This also mitigates concerns about simultaneity bias in the estimation.

Furthermore, we excluded the financial sector from the baseline specification. The rationale is that the financial sector may behave fundamentally differently from real sectors in terms of credit intermediation. First, banks rarely extend traditional commercial loans to financial institutions in the same way they lend to firms in manufacturing or services. Second, financial firms often have closer regulatory relationships with banks and central banks, which could bias estimates of lending behavior.

Table 2. Baseline specifications

	New loan issuance		**Loan outstanding**	
	$Ln(New)$	$Ln(New)$	$Ln(Outst)$	$Ln(Outst)$
	(1)	(2)	(3)	(4)
	monthly	quarterly	monthly	quarterly
Market share*Industry distress	**0.006****	**0.008***	-0.003	-0.008
	-0.003	(0.004)	-0.004	(0.008)
Market share	**0.04*****	**0.04*****	**0.08*****	**0.09*****
	(0.001)	(0.002)	(0.005)	(0.009)
Constant	6.86***	7.72***	8.35***	8.22***
	(0.02)	(0.035)	(0.06)	(0.119)
Bank-period FE	Yes	Yes	Yes	Yes
Industry-period FE	Yes	Yes	Yes	Yes
Obs	10377	3753	15344	4833

Notes: *Market share is lagged by 6 months and industry distress is lagged by 3 months in the monthly panel models. For the quarterly specifications, this corresponds to two quarters and one quarter, respectively.* ***, ** *and* * *denote significance at the 1%, 5% and 10% level, respectively.*

Column 1 of Table 2 presents our main baseline result using monthly panel dataset. The interaction term between market share and distress indicator is positive (0.006) and statistically significant, suggesting that banks with high market shares tend to issue more loans to an industry when it is in distress. In addition, the coefficient on market share alone is positive (0.04) and statistically significant, indicating that highercredit concentration is associated with increased loan issuance regardless of whether the industry is distressed. These baseline findings are consistent with the results of (Mariassunta & Farzad, 2018). Importantly, these results do not imply that certain banks such as systemically important banks in the case of Mongolia- lend more than others in general. This is because we included the bank-period fixed effects to control for any time-varying bank-level heterogeneity. Similarly, industry-period fixed effects are included to account for industry-specific characteristics beyond the distress indicator.

To assess robustness, we also estimate the baseline specification using a quarterly panel dataset. Column 2 and 4 reports results of estimation using quarterly panel dataset. The quarterly estimates are consistent with the monthly baseline results. While the loan outstanding regressions show a similarly positive and significant effect of market share on lending, the interaction term between market share and distress is not statistically significant in these specifications. This may be because financial distress is harder to detect when using stock variables like loan outstanding, as changes tend to be more gradual compared to flow variables such as newly issued loans, which more immediately reflect shifts in bank lending behavior.

4.2 Industry efficiency specifications

To further examine the role of industry characteristics in shaping bank lending behavior, we extend our baseline specification by interacting the market share–distress term with industry-level efficiency indicators: the asset-liability ratio (a proxy for solvency risk) and the asset turnover ratio (a proxy for operational efficiency). This specification is motivated by two assumptions. First, we expect that financially sound industries those with stronger balance sheets and more efficient operations will generally have better access to credit. Second, we investigate whether such financial strength continues to positively influence bank lending even during periods of industry-level distress.

The results are presented in Table 3. Column (1) shows that the triple interaction between market share, distress, and the asset-liability ratio is positive and statistically significant (0.008), indicating that banks with high market shares are more likely to continue lending to distressed industries that also exhibit stronger balance sheet positions. In contrast, the negative coefficient on the market share–asset-liability ratio interaction (-0.006) suggests that banks lend less to sectors with weak solvency, regardless of distress. Similarly, in Column (4), we find that the interaction of market share, distress, and asset turnover is positive and significant (0.026), while the direct interaction between market share and asset turnover is negative and significant (-0.018). These results imply that banks selectively extend credit to distressed industries that are more operationally efficient, while pulling back from sectors with low turnover ratios. Overall, these findings suggest that bank lending responses to industry distress are not uniform but depend on the underlying financial health and efficiency of the affected sector. This highlights banks' tendency to internalize credit risk more cautiously by favoring distressed yet fundamentally sound industries.

Table 3. Industry efficiency specifications

	New loan issuance		**Loan outstanding**	
	$Ln(New)$	$Ln(New)$	$Ln(Outst)$	$Ln(Outst)$
	(1)	(2)	(3)	(4)
	monthly	monthly	monthly	monthly
Market share*Industry distress	0.004	**0.010****	-0.004	-0.003
	(0.004)	(0.004)	(0.085)	(0.005)
Market share	**0.049*****	**0.025*****	**0.049*****	**0.085*****
	(0.003)	(0.003)	(0.003)	(0.007)
Market share*Industry distress *Asset liability ratio	**0.008*****		**0.006***	
	(0.002)		(0.002)	
Market share*Asset liability ratio	**-0.006*****		-0.003	
	(0.001)		(0.001)	
Market share*Industry distress *Asset turnover ratio		0.008		**0.026***
		(0.008)		(0.016)
Market share*Asset turnover ratio		**0.033*****		**-0.018*****
		(0.006)		(0.007)
Constant	6.64***	6.65***	8.15***	8.23***
	(0.032)	(0.032)	(0.076)	(0.063)
Bank-period FE	Yes	Yes	Yes	Yes
Industry-period FE	Yes	Yes	Yes	Yes
Obs	7198	7198	10746	10746

Notes: *Market share is lagged by 6 months and industry distress, asset liability ratio, and asset turnover ratio are lagged by 3 months in the monthly panel models. For the quarterly specifications, this corresponds to two quarters and one quarter, respectively.* ***, ** *and* * *denote significance at the 1%, 5% and 10% level, respectively.*

4.3 Supply chain effect specifications

To explore the potential amplification of credit shocks through supply chain linkages, we further extend our baseline specification by interacting the market share–distress term with industry-level supplier and customer shares[4]. This approach tests whether banks internalize spillover risks and adjust credit supply not only in response to direct distress but also based on a sector's position within the broader production network. The results are presented in Table 4. Columns (2) and (4) show that the triple interaction between market share, industry distress, and **supplier share** is positive and statistically significant in both monthly (0.040) and quarterly (0.032) estimations, suggesting that banks with high market shares tend to

[4] *We calculate the proportion of each industry's total inputs supplied by other sectors, as well as the share of its outputs consumed by downstream industries from the Input-Output (I-O) table. See Data section for details.*

continue lending to distressed industries that are central suppliers in the economy. This finding supports the hypothesis that banks internalize upstream production risks and extend credit to stabilize supply chains. In contrast, the interaction term involving **customer share** is negative and statistically significant in quarterly estimation (-0.021), implying that banks may be more cautious in lending to distressed industries with a large share of downstream dependence. These results highlight that supply chain structure matters for credit allocation: banks are more willing to support distressed input-supplying industries than output-distributing ones, possibly reflecting concerns over broader production disruptions and the relative difficulty of replacing upstream suppliers.

Table 4. Supplier and customer share inclusive specifications

	New loan issuance			
	$Ln(New)$	$Ln(New)$	$Ln(New)$	$Ln(New)$
	(1)	(2)	(3)	(4)
	monthly	monthly	quarterly	quarterly
Market share*Industry distress	0.02	**-0.026*****	0.028	**-0.021****
	(0.016)	(0.007)	(0.023)	(0.010)
Market share	**0.039*****	**0.039*****	**0.041*****	**0.042*****
	(0.002)	(0.002)	(0.003)	(0.003)
Market share *Customer share *Industry distress	-0.02		-0.028	
	(0.018)		(0.027)	
Market share*Supplier share *Industry distress		**0.037*****		**0.032*****
		(0.008)		(0.011)
Constant	6.65***	6.64***	7.50***	7.49***
	(0.029)	(0.029)	(0.040)	(0.040)
Bank-period FE	Yes	Yes	Yes	Yes
Industry-period FE	Yes	Yes	Yes	Yes
Bank-Industry FE	Yes	Yes	Yes	Yes
Obs	8579	8843	3317	3317

Notes: *Market share is lagged by 6 months and industry distress, supplier share, and customer share are lagged by 3 months in the monthly panel models. For the quarterly specifications, this corresponds to two quarters and one quarter, respectively.***, ** and * denote significance at the 1%, 5% and 10% level, respectively.*

4.4 Robustness test

We conducted several robustness checks to ensure the reliability of our results. These included (i) replicating the analysis using quarterly panel data, (ii) incorporating bank-industry fixed effects, and (iii) restricting the sample size by excluding two small banks.

First, we re-estimated the baseline specifications using quarterly panel dataset, as shown in column 2, 4 in Table 2. This approach tests whether our findings hold when short-term fluctuations in loan issuance and distress indicators are smoothed. As expected, the results are consistent with the monthly estimates, confirming the robustness of our main findings across different data frequencies.

Second, we augmented the baseline model by including the bank-industry fixed effects to control for unobserved, time-invariant heterogeneity in bank-industry relationships. In this case, the interaction term between market share and distress remains positive and significant for the newly issued loans, while market share coefficient becomes insignificant, likely because the persistent lending relationships are now absorbed by the fixed effects.

Lastly, we restricted the sample by excluding two small banks, which exhibited extreme outlier values in new loan issuance due to their limited lending volume. As shown in Table 6, the main results remained robust, suggesting that our findings are not driven by outliers or small-bank dynamics.

V. Conclusion

This study investigates how credit concentration influences bank lending behavior during periods of industry-level financial distress in Mongolia. Using a unique bank-industry-time panel dataset from the Bank of Mongolia covering the years 2017–2024, we provide robust empirical evidence that banks with higher market shares in a given sector are more likely to maintain or increase lending when that sector experiences financial distress. This finding suggests that dominant lenders play a stabilizing role by internalizing sector-specific risks and mitigating the potential for broader financial contagion.

Our analysis also shows that this stabilizing behavior is not indiscriminate. Rather, it is shaped by the underlying financial health of distressed industries. Banks are more inclined to extend credit to sectors with stronger solvency and operational efficiency, as reflected in the asset-liability and asset turnover ratios. This indicates that credit concentration, when paired with sectoral risk assessments, leads to more targeted and risk-sensitive lending strategies, particularly important in a banking system like Mongolia's, where a few banks hold significant market power.

Additionally, we explore how supply chain linkages influence credit allocation during distress episodes. Our results reveal that banks with large exposures to key input-supplying industries are more likely to support these sectors during downturns, recognizing their central role in the broader production network. In contrast, distressed industries with large customer dependencies do not receive the same level of credit support, suggesting that banks differentiate between upstream and downstream risks when allocating credit under stress.

The robustness of these findings across alternative specifications, data frequencies, fixed effects, and sample restrictions strengthens the conclusion that credit concentration, while often viewed as a source of systemic vulnerability, can also serve as a stabilizing force when accompanied by proper incentives and sectoral awareness.

These insights have important implications for financial stability and macroprudential policy. They call for a more nuanced understanding of bank concentration recognizing its potential to absorb shocks rather than amplify them and for the design of regulatory frameworks that support incentive-compatible lending without exacerbating systemic risk. Policymakers should closely monitor sector-level credit dynamics and financial health indicators to inform timely, targeted interventions that safeguard credit provision during downturns.

Future research could deepen this line of inquiry by examining the propagation of credit shocks through supply chains, using network-based methods and firm-level data. Such approaches would offer richer insight into how financial distress transmits across industries, especially in economies with dense inter-sectoral dependencies.

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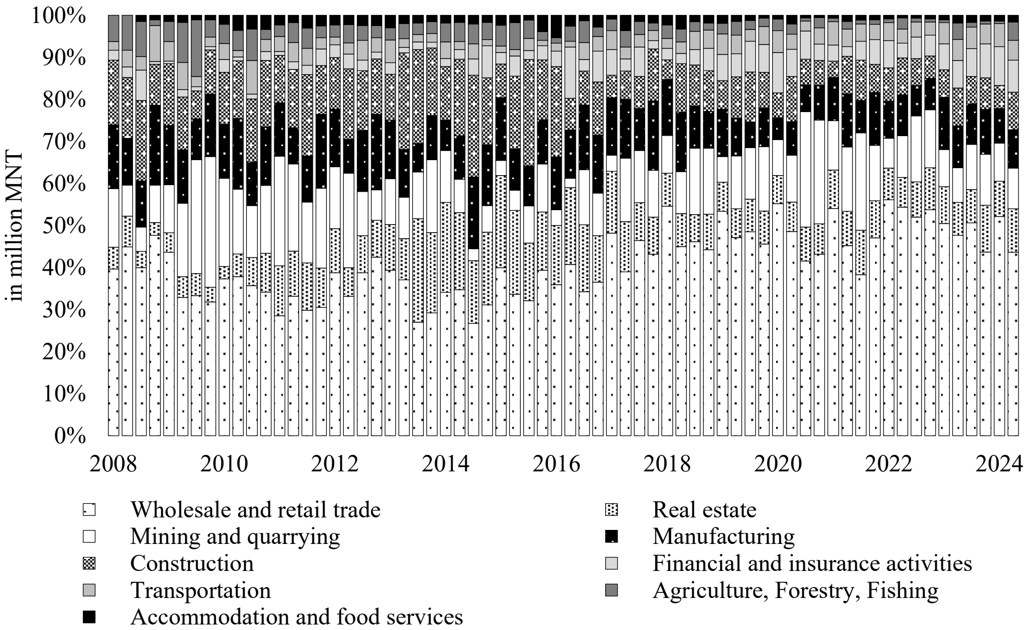
Appendix

Appendix 1. Summary of the Dataset

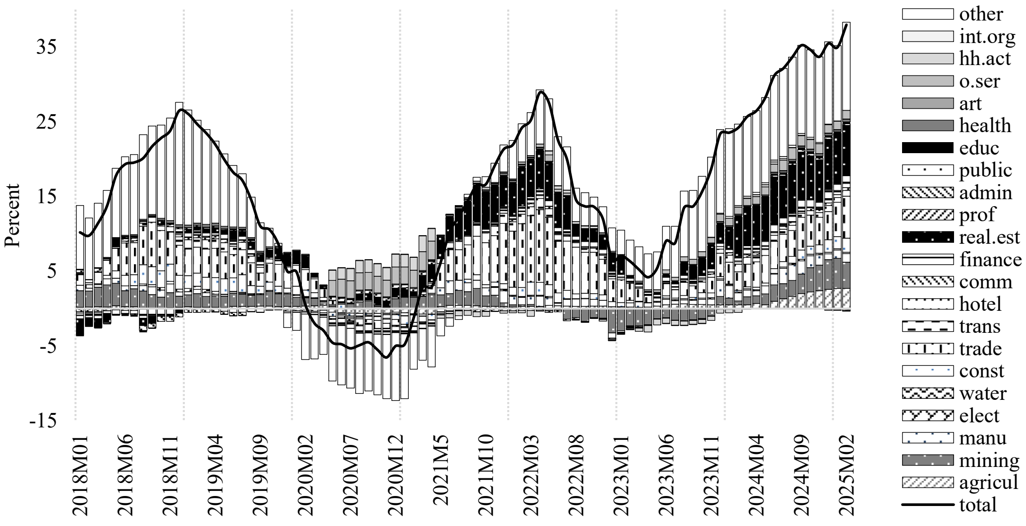
Variable name	Variable definition	Source	Data range availability
Bank-industry-time level dataset			
New loans	New loans issued at time t from bank i to industry j	Bank of Mongolia	M: 2017-2024
Loan outstanding	Loan outstanding of bank i to industry j at time t	Bank of Mongolia	M: 2017-2024
New loan growth	YoY change in the new loans issued from bank i to industry j at time t	Bank of Mongolia	M: 2017-2024
Loan outstanding growth	YoY change in the loans outstanding of bank i to industry j at time t	Bank of Mongolia	M: 2017-2024
Market share	Bank i's share in total loan outstanding in industry j at time t	Bank of Mongolia	M: 2017-2024
Industry-time level dataset			
NPL ratio	Share of non-performing loans in total loan outstanding of industry j at time t	Bank of Mongolia	M: 2017-2024
Distress indicator	Equal 1 if NPL share > (median + 1std), 0 otherwise	Bank of Mongolia	M: 2017-2024
Asset, liabilities ratio	(total liabilities / total assets)*100	Ministry of Finance	A: 2017-2022
Asset turnover ratio	(total operating revenue /total assets)*100	Ministry of Finance	A: 2017-2022
Supplier share	Share weighted by each input industry's share in the total input supply to industry j	National Statistics Office: I-O table	A: 2017-2019
Customer share	Share weighted by each receiving industry's share in total demand for industry j's output	National Statistics Office: I-O table	A: 2017-2019

Appendix 2. Share of new loan issuance of major borrowing industries in total loan issuance



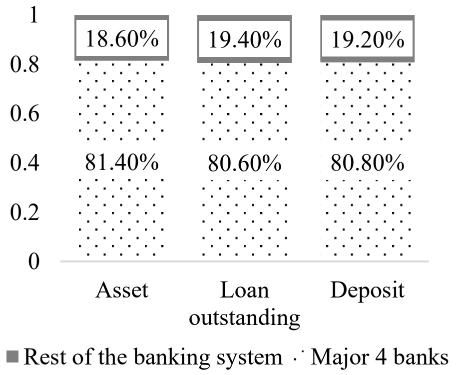
Source: Bank of Mongolia

Appendix 3. Loan outstanding growth by industries

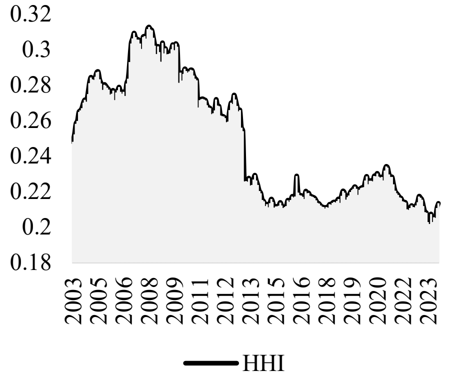


Source: Bank of Mongolia

Appendix 4. Major 4 banks'share in the market, June 2024

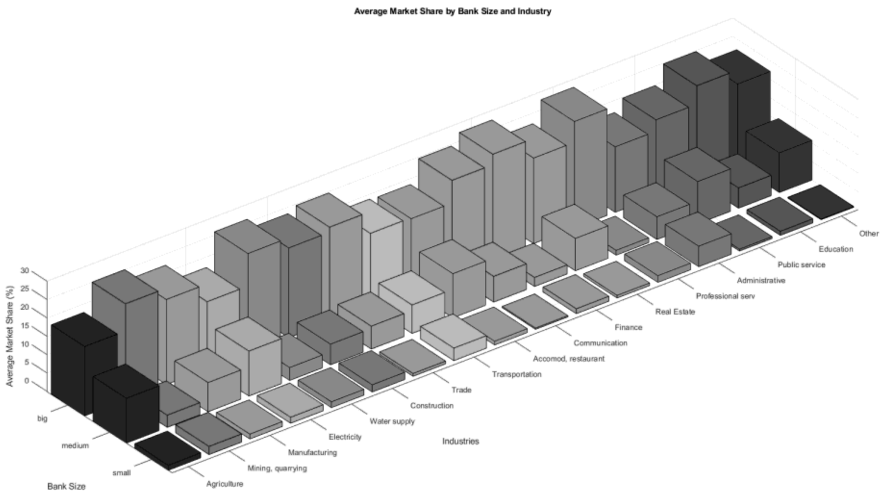


Appendix 5. HHI index



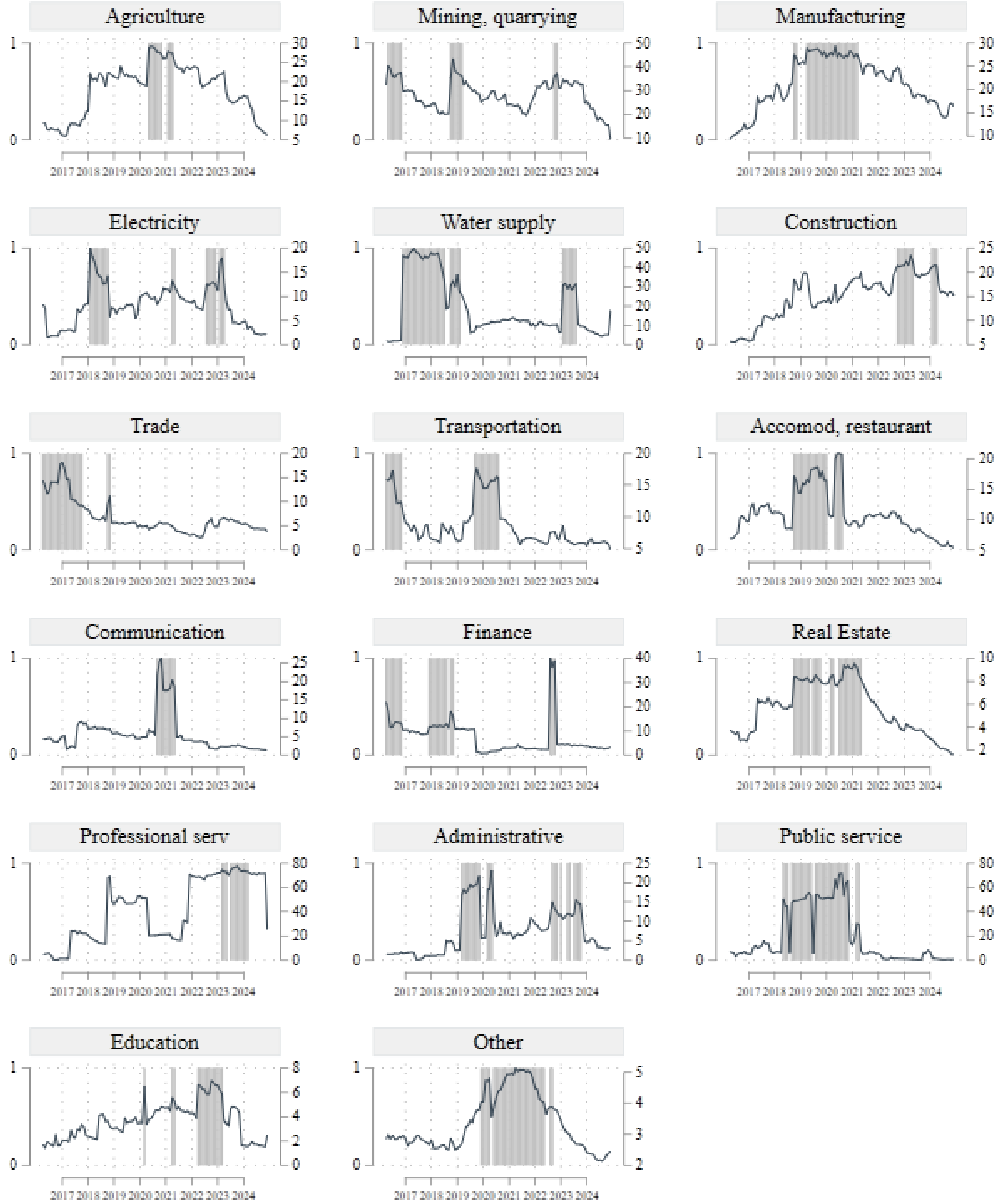
Source: Bank of Mongolia Source: Bank of Mongolia, Researchers' calculation

Appendix 6. Average market share, by bank size and industry



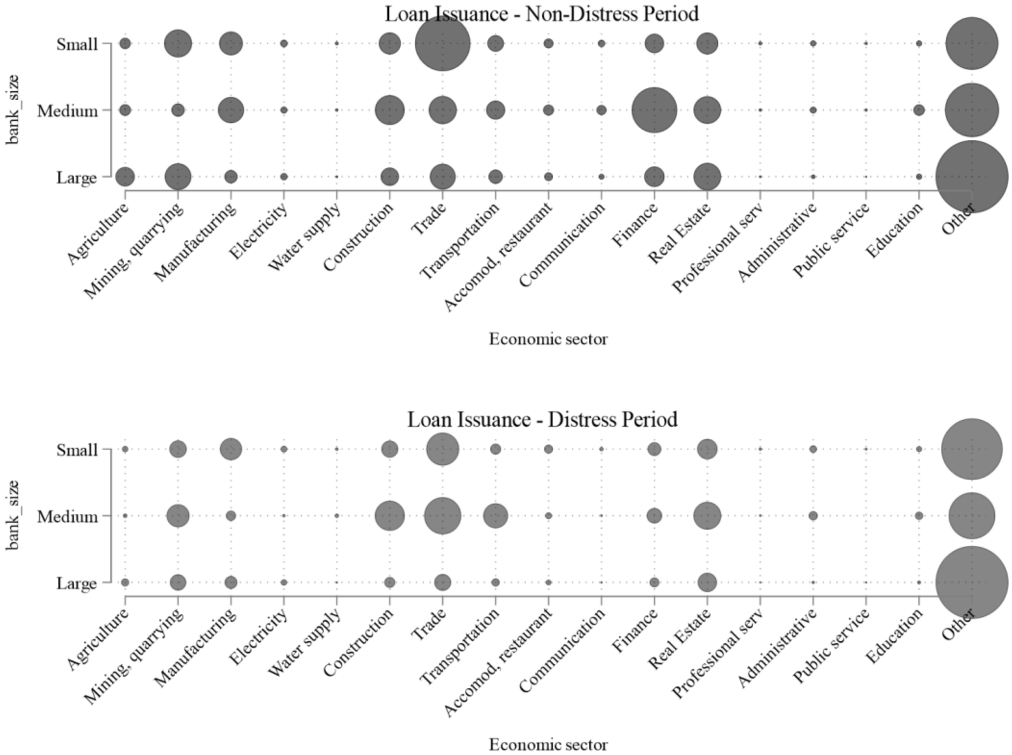
Source: Bank of Mongolia, Researchers' compilation

Appendix 7. Distress indicator and NPL ratio, by economic sectors



Note: *Grey shaded areas indicate our defined distress periods and navy line indicate the NPL ratio.*
Source: Bank of Mongolia, Researchers' calculation

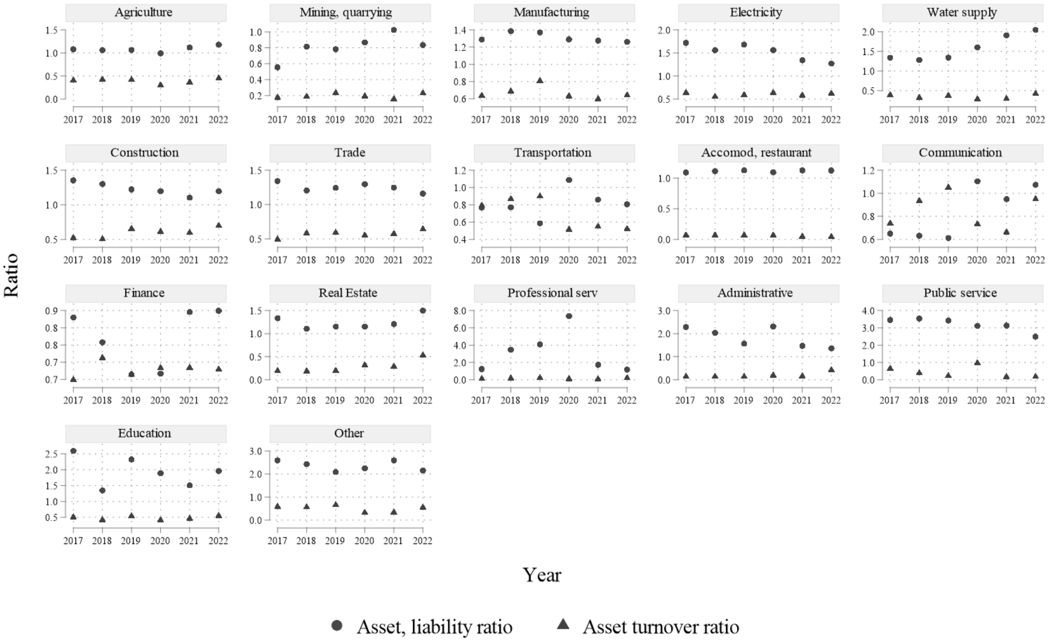
Appendix 8. Average Loan Issuance by Bank size and Industry, Non-Distress vs Distress Period



Source: Researchers' calculation

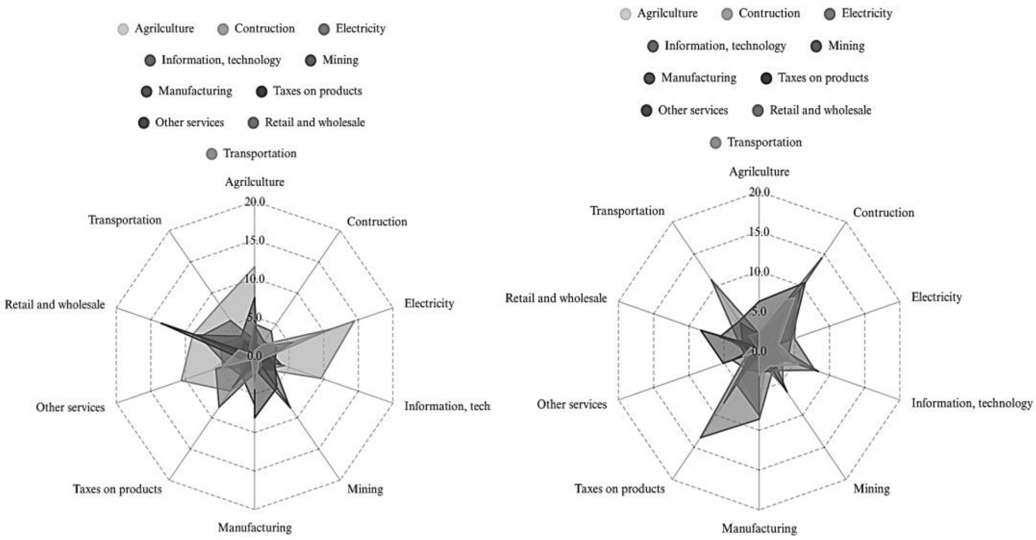
Appendix 8 provides a visual summary of loan issuance by bank size and economic sector, distinguishing between non-distress (top panel) and distress (bottom panel) periods. The size of each bubble represents the average volume of newly issued loans from banks of different sizes (small, medium, large) to each sector. During non-distress periods, large banks dominate lending activity, particularly in trade, finance, and the "other" sectors, with significant issuance also observed from medium-sized banks in communication and finance. However, during distress periods, lending volumes contract substantially across all bank sizes and sectors, with noticeable reductions even in previously active sectors. While large banks still maintain relatively higher issuance levels, especially in trade and the "other" category, the overall decline illustrates a more cautious lending stance during industry downturns. This figure highlights both the concentration of credit supply in certain sectors and how lending behavior shifts depending on macro-financial conditions.

Appendix 9. Industry Efficiency Ratios



Source: Ministry of Finance, Researchers' compilation

Appendix 10. Contribution to other sectors



Source: I-O table 2019, National Statistics Office, Researcher's compilation

Appendix 9 and 10 illustrate the connectedness of the economic sectors in Mongolia. Construction, manufacturing and transportation sectors were dominant in terms of contributing to the productions of other sectors while the retail trade and the electricity sectors were the most dependent from other economic sectors.

Appendix 11. Robustness: Market share and industry distress (Bank-Indusrry FE included)

	New loan issuance		**Loan outstanding**	
	$Ln(New)$	$Ln(New)$	$Ln(Outst)$	$Ln(Outst)$
	(1)	(2)	(3)	(4)
	monthly	quarterly	monthly	quarterly
Market share*Industry distress	0.002	0.006**	-0.004	-0.008
	(0.002)	(0.004)	(0.004)	(0.006)
Market share	-0.001	-0.004	0.021***	0.016**
	(0.002)	(0.004)	(0.004)	(0.008)
Constant	7.35***	8.29***	8.93***	8.94***
	(0.035)	(0.048)	(0.040)	(0.084)
Bank-period FE	Yes	Yes	Yes	Yes
Industry-period FE	Yes	Yes	Yes	Yes
Bank-Industry FE	Yes	Yes	Yes	Yes
Obs	10365	3745	15342	4833

****, ** and * denote significance at the 1%, 5% and 10% level, respectively.*

Appendix 12. Robustness: Market share and industry distress (Outlier banks are excluded)

	New Loan issuance		**Loan outstanding**	
	$Ln(New)$	$Ln(New)$	$Ln(Oust)$	$Ln(Outst)$
	(1)	(3)	(2)	(4)
	monthly	quarterly	monthly	quarterly
Market share*Industry distress	0.001	0.004	-0.009**	-0.016**
	(0.002)	(0.003)	(0.004)	(0.007)
Market share	0.04***	0.04	0.07***	0.08***
	(0.001)	(0.002)	(0.004)	(0.008)
Constant	6.93***	7.85***	8.48***	8.34***
	(0.023)	(0.035)	(0.056)	(0.118)
Bank-period FE	Yes	Yes	Yes	Yes
Industry-period FE	Yes	Yes	Yes	Yes
Obs				

****, ** and * denote significance at the 1%, 5% and 10% level, respectively.*