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Sectoral Concentration in Loans and Credit Risk: An Examination by Company Accounts in Turkey

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Abstract

This study examines the impact of sectoral concentration on credit default risk, drawing from economic theory and portfolio management principles, utilizing the Turkish aggregated sector-level data and banking data from 2009 to 2022. The study employs a panel data analysis framework to investigate the relationship between sectoral diversification in loans and credit risk, controlling for sector-specific variables. Unlike previous studies primarily reliant on banking system data, this research broadens the scope by incorporating the real sector credit usage data for the measurement of concentration. Additionally, instead of the commonly used Herfindahl-Hirschman Index, the study employs the Sector Concentration Index as a measure of concentration, allowing for a comparison of sector distribution with an ideal market sector distribution. The analysis considers not only the widely used indicator of credit risk, non-performing loans ratio in the banking system but also bad debt ratios in the real sector, thereby enhancing the understanding of credit risk dynamics. The analysis results, which show a significant positive relationship between sectoral concentration indices and non-performing ratios employed, reveal that sectoral credit concentration has an increasing effect on the credit risk level and offers insights into the optimal diversification strategies for mitigating credit risk in the banking sector.

Keywords: Sectoral Loan Concentration, Sectoral Loan Diversification, Credit Default Risk, Turkish Company Accounts, Turkish Banking Sector, Panel Data Analysis.

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1. INTRODUCTION

As economic theory suggests, increased diversity tends to reduce volatility, a principle most notably observed in portfolio theory. According to portfolio theory, diversification minimizes the overall risk of a portfolio through strategic asset allocation, maintaining expected returns as long as assets are not perfectly correlated (Markowitz, 1952). Conroy (1974) extended portfolio theory to regional and economic growth and instability, suggesting that sectoral diversification would enhance a region's overall economic stability and efficiency and thus serving as insurance against volatility in various industries. The impact of sectoral diversification on economic and financial instability has been the subject of recent research (Kluge, 2018, pp. 205-206).

In banking, credit risk concentration arises when loans are extended to counterparties within the same economic sector or geographic region (Banking Regulation and Supervision Agency [BRSA], 2016). Given that lending is a core function of banks and key intermediaries in financial markets, the level, causes, and effects of sectoral diversification on credit risk merit thorough investigation.

Financial intermediation theories highlight intermediaries' cost advantages offer in resolving agency problems between borrowers and lenders. A financial intermediary, such as a bank, collects funds from depositors (lenders) and lends them to entrepreneurs (borrowers), taking on the crucial task of monitoring these loans and assessing borrower credibility on behalf of depositors (Winton, 1999). Diversifying a loan portfolio provides essential cost advantages for intermediaries in their delegated monitoring roles, as it allows for a higher risk tolerance toward individual loans, ultimately reducing the cost of risk-bearing incentives (Diamond, 1984). This conventional view suggests that well-diversified financial intermediaries minimize default probabilities and enhance loan returns by lowering the need for costly equity capital (Diamond, 1984; Winton, 1999).

However, while diversification across multiple sectors and regions may lower asset risk by improving monitoring incentives, it does not guarantee low risk. Expanding into new sectors, geographies, and loan types can dilute expertise, potentially weakening monitoring effectiveness and making diversification costly. Studies advocating for concentration in bank lending cite benefits such as enhanced screening and monitoring efficiency (Beck & De Jonghe, 2013; Winton, 1999). Concentration can mitigate asymmetric information problems by allowing banks to specialize in familiar areas (Anastasi et al., 2009; Sarı & Konukman, 2021; Sarı & Konukman, 2023; Winton, 1999).

While competitive pressures may make diversification appealing, they can also compel banks to venture into sectors lacking expertise (Winton, 1999). Although sectoral concentration can improve a bank's performance during specific economic conditions, it may simultaneously elevate systemic risk and the fragility of financial institutions (BRSA, 2016; Demirbaş Özbekler, 2019; Yalçın & Tunay, 2020), thereby threatening overall financial stability. Furthermore, the reliance on wholesale funding and interbank market activities, exacerbated by complex financial products and globalization, has intensified banks' sensitivity to credit volatility and market fluctuations, introducing additional contagion risks (BRSA, 2016). It is crucial for banks to adopt contemporary portfolio management strategies that align credit portfolios with the market's optimal structure to mitigate these risks, thereby shielding against systemic risks (Yalçın & Tunay, 2020; Gönenç & Kılıçhan, 2004).

This study investigates the impact of sectoral concentration in credits given to the Turkish real sector and its 17 sub-sectors on credit default risk during the period 2009-2022. Our research is distinguished by two key features: applying a concentration measure that aligns credit portfolios with the market's ideal portfolio and using aggregated sector-level data rather than solely relying on bank-level data.

In the literature, the Herfindahl-Hirschman Index (HHI), developed by Herfindahl (1959) and Hirschman (1964), has been widely used to measure sectoral concentration levels. The HHI is calculated as the sum of the squared relative credit risk positions, but it does not account for comparisons with an ideal portfolio distribution. However, portfolio management theory suggests that aligning credit portfolios with optimal sector distributions can mitigate systemic risk (Gönenç & Kılıçhan, 2004; Hazar et al., 2017). Notably, all ten studies (Gönenç & Kılıçhan, 2004; Türkmen & Yiğit 2012; Tunay, 2015; Demirbaş Özbekler, 2019; Sarı 2019; Sarı,2020; Yalçın & Tunay, 2020; Sarı & Konukman 2021; Sarı, 2022; Sarı & Konukman, 2023) examining Turkey's economy included in this research have employed the HHI, with only Gönenç and Kılıçhan (2004) additionally using standard deviation as suggested by the ideal credit volume model.

This study employs the Sector Concentration Index (SCI), a corrected version of HHI according to the market (Kacperczyk et al., 2005, p. 1987) that facilitates comparisons of sector distribution with optimal allocations. In this study, the relative asset size, number of firms, and GDP contribution of sectors have been used as three different ideal credit distribution portfolios.

These ten studies for the Turkish economy utilized bank-level data in concentration measurements and other variable constructions and did not consider borrower-side (firm or sector side) factors. Unlike previous studies primarily reliant on banking system data, this research broadens the scope by incorporating real sector credit usage data. Real sector data has been employed in measuring sectoral loan concentration indices and used as an alternative to bank-level data in assessing credit risk, and as a control variable for sector risk, thereby accounting for the characteristics of the real sector as the borrower of loans. This comprehensive data, which combines bank data with real sector dynamics, contributes to the existing literature by providing insights into the nuanced relationships between sectoral factors and credit risk.

Following theoretical background, the subsequent sections will delve into the methodology employed, including sample selection, variable definitions, dataset development, and the econometric framework utilized in the analysis.

2. THEORETICAL GROUNDING

Some studies on concentration in bank lending and their effects have yielded results in favor of diversification, while others have supported concentration.

Among the studies supporting sectoral diversification, Kluge (2018) focused on the positive effect of sectoral diversification on economic stability and growth in regions of Germany, while Morgan and Stolyk (2003) emphasized that geographic diversification among U.S. holding banks increased the banking system's lending capacity. Using international data, Beck and De Jonghe (2013) found that sectoral diversification in bank lending had a positive impact on bank performance, increasing returns or reducing risk. Bebczuk and Galindo (2008) reached similar conclusions with data from Argentina, while Chen et al. (2013) noted that although sectoral diversification reduced bank risk, it also decreased returns. The findings of Bebczuk and Galindo (2008) were particularly pronounced during downturns in the business cycle and in larger banks.

On the other hand, among the studies that present findings in favor of specialization, Winton (1999) demonstrated that sectoral or regional diversification in bank lending, under certain conditions, such as moderate risk, can reduce the probability of bank failure. However, when loans have either low or high downside risk, diversification adds little value or may even increase the odds of bank failure. Acharya, Hasan, and Saunders (2006) concluded that sectoral diversification in high-risk or new/competitive industries diminishes the monitoring effectiveness of Italian banks. Conversely, Böve, Düllmann, and Pfingsten (2010) found that the monitoring quality of German cooperative and savings banks improved with sectoral specialization. Similarly, Anastasi et al. (2009) for Argentine financial institutions and Tabak, Fazio, and Cajueiro (2011) for Brazilian banks related loan portfolio concentration to reduced default risk, while Goetz (2012) highlighted the increased risk associated with diversification among international markets.

Studies on Turkish data also tend to yield mixed results either in favor of diversification and/or concentration. Among studies examining the effect of sectoral concentration on bank profitability, Türkmen and Yiğit (2012) found that sectoral concentration had a decreasing effect on bank profitability (ROA and ROE), Gönenç and Kılıçhan (2004) and Sarı (2020) demonstrated that sectoral and geographical loan concentration increase banks profitability.

We have identified five studies directly examining the relationship between diversification and credit risk with Turkish data. Among them, while three studies (Tunay, 2015; Sarı, 2019; Yalçın & Tunay, 2020) concluded that diversification reduces credit risk, only one accessible study (Sarı & Konukman, 2021) obtained a negative relationship between that sectoral diversification and credit risk in the Turkish banking system. However, Demirbaş Özbekler (2019) suggests that the direction of the relationship varies depending on the method used. The last two studies presented in this section focus on the effect of geographical diversification (Sarı, 2022) and the relationship between sectoral concentration and GDP growth (Sarı and Konukman, 2023). Sarı (2022) gathered a negative relationship between geographical concentration and credit risk in the long run. Sarı and Konukman (2023) showed a bidirectional positive relationship between sectoral loan concentration and economic growth.

In the ten studies this research summarized and conducted using data from the Turkish banking system, the level of sector concentration in loans was calculated using the Herfindahl-Hirschman Index (HHI). The HHI ($\mathrm{HII_t} = \sum_{\mathrm{i}=}^{\mathrm{n}} (W_{\mathrm{i,t}})^2$) is derived from the sum of the squares of the relative shares of loans provided to specific sectors by the banks or bank groups in the sample. The HHI, which takes values between 0 and 1, indicates that as it approaches 1, the loans of the examined bank or banking group are concentrated in specific sectors, suggesting a lack of diversification. As inferred from its formula, the HHI does not account for an ideal sectoral loan distribution. However, in portfolio theory, the effectiveness of diversification is achieved by the portfolio's convergence towards an optimal market portfolio. In the study by Gönenç and Kılıçhan (2004), in addition to the HHI, the level of diversification was measured by standard deviation that indicates how much the bank deviates from the market portfolio, which is considered the ideal distribution on a sectoral basis (Gönenç & Kılıçhan, 2004, p. 60).

In this study, the Sector Concentration Index (SCI), originally introduced by Kacperczyk et al. (2005) to assess the industry concentration of mutual funds, was utilized. The SCI serves as a modified version of the Herfindahl-Hirschman Index (HHI), tailored to reflect market conditions, and is employed to evaluate concentration in relation to the ideal sector distribution. The SCI measures the deviation from the market portfolio, with higher index values indicating a greater concentration in a limited number of industries (Kacperczyk et al., 2005, p. 1987).

Besides utilizing a different measure of concentration, this study also contributes to the previous research conducted in Turkey by employing a more comprehensive dataset. The ten studies mentioned calculated the concentration of loans provided to various sectors using data from the Turkish banking system. Similarly, the relationship between loan concentration and bank performance was analyzed exclusively using bank-level data. Therefore, factors related to firms or sectors as recipients of credit were not considered in these studies. In this research, however, data specific to the real sector, which is the borrower of bank loans, was utilized both for measuring sectoral concentration indices and for determining other relevant variables.

3. DATA AND METHODOLOGY

This section details the sample selection, dataset development, and the econometric framework employed in the analysis.

3.1. Sample and Variables

The study employs panel data analysis using information from the Central Bank of the Republic of Turkey (CBRT), the Banking Regulation and Supervision Agency (BRSA), and the Turkish Statistical Institute (TSI). The data were collected from various sources, including CBRT statistics (CBRT, 2023), BRSA statistics (BRSA, 2023), and TSI data (TSI, 2023). Sector data are aggregated and included in the CBRT sector balance sheets. The data for all sectors combined is referred to as 'all companies' (hereinafter referred to as the real sector). Annual balance sheets, income statements, and sector risk data for the real sector and 17 main sectors for the period 2009-2022 were compiled. The analysis covers 17 sectors over 14 years, yielding 238 observations. After 2008, the sector distribution in the CBRT matches that of the TSI's Gross Domestic Product (GDP). Three of the 20 sectors reported by TSI are not included in the CBRT data, so the analysis was conducted with the 17 sectors reported by the CBRT.

In the previous literature, credit risk is typically proxied by non-performing loans (NPL) rate or bad debt rate (Anastasi et al., 2009; Tunay, 2015; Demirbaş & Özbekler, 2019; Yalçın &Tunay, 2020) or NPL amounts (Sarı, 2019; Sarı & Koruman, 2021; Sarı, 2022). In this study, three alternative NPL ratios representing the real sector were used as time-variant but sector-invariant variables:

NPL_{t_1}: Ratio of "Banking Sector Non-Performing Loans / Total Cash Loans (%)" for the Turkish banking sector (Total loans and non-performing loan amounts are gathered from BRSA balance sheet information and monthly banking sector data).

NPL_{t_2}: "Banking Sector Non-Performing Loans (Gross) / Total Cash Loans (%)" ratio (Directly obtained from BRSA's monthly banking sector ratio information).

NPL_{t_3}: "Real Sector Bad Debts / Cash and Non-Cash Credits" ratio (Calculated using data from the CBRT's company accounts statistics).

According to BRSA (2016), the types of loans that lead to credit risk concentration are as follows: i. Large amounts loans extended to the same counterparties or ii. Groups consisting of counterparties with risk relationships among them. iii. Loans extended to counterparties located in the same economic sector or geographical region. iv. Loans extended to groups of counterparties engaged in the same service or goods production or utilizing the same credit risk mitigation methods, and v. Credit risks indirectly exposed due to the use of only one type of collateral or credit protection. This study focuses more on diversification in the third group.

In this study, the concentration measurement, referred to as standard deviation in the study by Gönenç and Kılıçhan (2004) and modeled as the Sector Concentration Index (SCI) in the study by Kacperczyk et al. (2005), was used. SCI (Kacperczyk et al., 2005, p. 1987) is the adjusted form of the Herfindahl-Hirschman Index (HHI) according to an optimal sector distribution criterion.

SCI is calculated using Equation (1):

Sector Concentration Index = $\mathrm{SCI_t} = \sum_{i=1}^{17} (W_{i,t} - \bar{W}_{i,t})^2$ (1)

Sector Concentration Index (SCI) is represented by Equation (1), where it $W_{i,t}$ denotes the share of the respective sector's credit risk (credit utilization) within the real sector's credit risk for the given year. Risk statistics of CBRT company accounts report the sector credits under categories of cash, non-cash credits, bad debts, bonds, commercial papers, and funds used for leasing. $\bar{W}_{i,t}$ represents the optimal or required share for the sector's credit share ($W_{i,t}$). $\bar{W}_{i,t}$ is determined based on three different assumptions regarding the sector's characteristics: asset size (AS), firm number (FN), and value-added (VA). Data for variables other than sectoral value added were obtained from the CBRT database.

Under the asset volume criterion, the Sector Concentration Index_AS (SCIt_AS) is constructed to ensure that credit allocation to each sector is aligned with its relative asset size within the real sector. The firm number assumption requires that credit be allocated based on the relative number of firms within each sector, forming an alternative Sector Concentration Index_FN (SCIt_FN). The third Sector Concentration Index_VA (SCI_t_VA) is derived from the sector's relative value added (gross domestic product) within Turkey's gross domestic product, as reported by TSI. The most commonly applied diversification measures are the sectoral distribution of employment or gross value added in a specific region (Kluge, 2018, p. 206). Value added share is obtained from the TSI database reported in the table of "Gross domestic product at current prices by kind of economic activity A21 level value, share, percentage change, at current prices, 1998-2022." (TSI, 2023). SCI_ts are specified annually and represent time-variant but sector-invariant variables.

As summarized in the literature review presented in Section 2, studies have not reached a consensus on whether sectoral diversification or concentration in bank loans reduces credit risk. However, in line with the majority of studies focusing on the relationship between credit risk and diversification using Turkish data (Tunay, 2015; Sarı, 2019; Yalçın & Tunay, 2020), it is hypothesized that there is a positive relationship between credit concentration and credit risk, forming Hypothesis 1 (H_1):

Hypothesis 1 (H_1): In year t, the higher the Sector Concentration Index of real sector credits (SCI_{it}), the higher the credit risk of the real sector (NPL_{it}).

Studies in this field are generally carried out on bank-level data, thus controlling for bank characteristics. Bank scale (Demirbaş Özbekler, 2019; Gönenç & Kılıçhan, 2004 Tunay, 2015; Türkmen & Yiğit 2012; Yalçın & Tunay, 2020), equity ratio and liquidity (Demirbaş Özbekler, 2019; Sarı 2019; Sarı, 2022; Sarı & Konukman 2021; Tunay, 2015) …etc. are used in these analyses.

In this study conducted with sectoral data, interest coverage ratio ($INTC_{it}$), chosen as the only control variable, represents the ratio of operating profit to financing expense for each sector at time *t*. It indicates the ability to generate income from core operations and meet financing expenses, thus signaling borrowing levels, borrowing costs, and investment profitability. A negative relationship between INTC and credit risk is expected.

Hypothesis 2 (H_2): In year t, a higher Interest coverage ratio of sector i ($INTC_{it}$) is associated with a lower credit risk of the real sector (NPL_{it}). Table 1 presents the summary of the analysis variables detailed in this section.

Table 1. Summary of Variables

Variable	Explanation	Source	Exp.Signs
NPL_1	Banking Sector NPL / Total Cash Loans	BRSA loans	DV
NPL_2	Banking Sector NPL (Gross) / Total Cash Loans	BRSA ratios	DV
NPL_3	Real Sector Bad Debts / Cash&Non-Cash Credits	CBRT company accounts	DV
SCI_AS	Sector Concentration Index_ Asset Size (AS)	CBRT company accounts	+
SCI_VA	Sector Concentration Index_Value Added (VA)	CBRT company accounts and TSI	+
SCI_FN	Sector Concentration Index_Firm Number (FN)	CBRT company accounts	+
INTC	Interest Coverage Ratio	CBRT company accounts	-

Note: NLP_1: Banking Sector Non-Performing Loans/Total Cash Loans. NPL_2: Banking Sector Non-Performing Loans (Gross)/Total Cash Loans. NPL_3: Real Sector Bad Debts/Cash and Non-Cash Credits. SCI_AS: Sector Concentration Index in terms of the sector's asset size (AS). SCI_VA: Sector Concentration Index in terms of value added (VA). SCI_FN: Sector Concentration Index in terms of firm number (FN). $INTC_{it}$ Interest coverage ratio. DV: Dependent Variable. Exp.: Expected.

3.2. Descriptive Statistics of Variables

This section presents the descriptive statistics of analysis variables in Table 2 and includes two graphs for two selected variables. The trend of NPL_1 throughout the analysis period is depicted in Figure 1, while the development of the concentration index of SCI_AS over 14 years is illustrated in Figure 2. Table 3 displays the correlation coefficients between independent variables. Besides, this section includes Table 4 which indicates in which direction and to what extent sectoral credit distribution deviates from the optimal credit rationing specified on sectoral asset volume.

Table 2. Descriptive Statistics of Variables

	Obs.	Mean	Std. Dev.	Min	Max
NPL_1	238	3.56	0.99	2.16	5.68
NPL_2	238	3.42	0.91	2.10	5.36
NPL_3	238	2.23	0.76	1.58	4.26
SCI_AS	238	51.75	16.75	28.19	79.79
SCI_VA	238	507.94	156.33	295.40	779.19
SCI_FN	238	490.22	77.21	388.82	664.50
INTC	238	1.57	1.44	-3.30	10.09

Note: NLP_1: Banking Sector Non-Performing Loans/Total Cash Loans. NPL_2: Banking Sector Non-Performing Loans (Gross)/Total Cash Loans. NPL_3: Real Sector Bad Debts/Cash and Non-Cash Credits. SCI_AS: Sector Concentration based on the sector's asset size (AS). SCI_VA: Sector Concentration Index in terms of value added (VA). SCI_FN: Sector Concentration Index in terms of firm number (FN). $INTC_{it}$ Interest coverage ratio. Obs.: Number of observations. Std. Dev.: Standard deviation. Min.: Minimum. Max.: Maximum.

According to descriptive statistics presented in Table 2, The NPL_1 mean value indicates that, on average, non-performing loans make up 3.56% of total loans in the banking sector. As shown in Figure 1, which depicts the development of non-performing loans (NPL_1) in the banking sector from 2009 to 2022, NPL_1 followed a horizontal trajectory between 2013 and 2017 but increased thereafter, peaking in 2019. The highest NPL ratio (5.68%) occurred in 2019, while the lowest ratio (2.16%) was recorded in 2022. The first two NPL ratios calculated from banking sector data (NPL_1 and NPL_2) appear to have similar means and standard deviations. However, NPL_3 which is measured by real sector data appears to have a lower mean and standard deviation, indicating potentially different measurement methods and criteria. NPL_3 mean value represents that bad debts account for 2.23% of total real sector credit. NPL_3 reached the maximum level of 4.26% in 2019 as in NPL_1 and NPL_2.

Figure 1: Trend of NPL_1

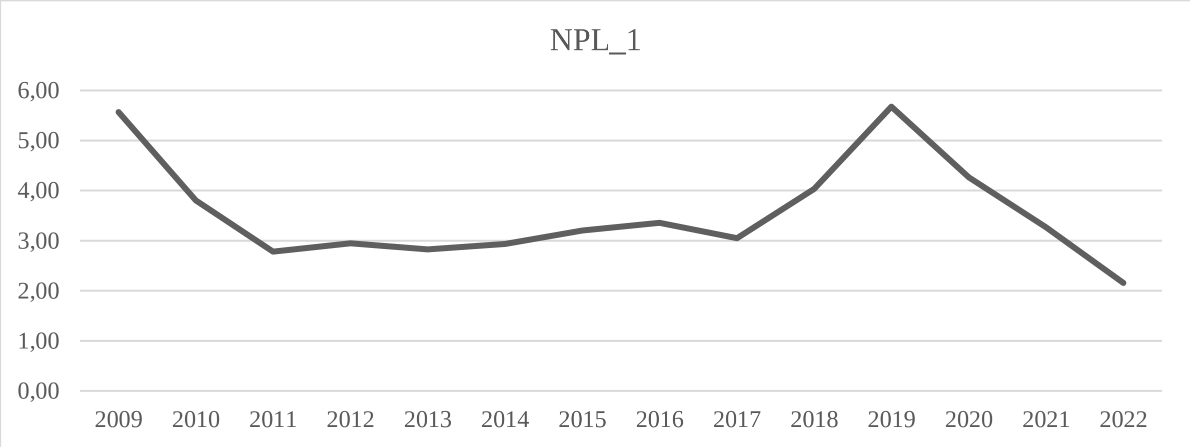
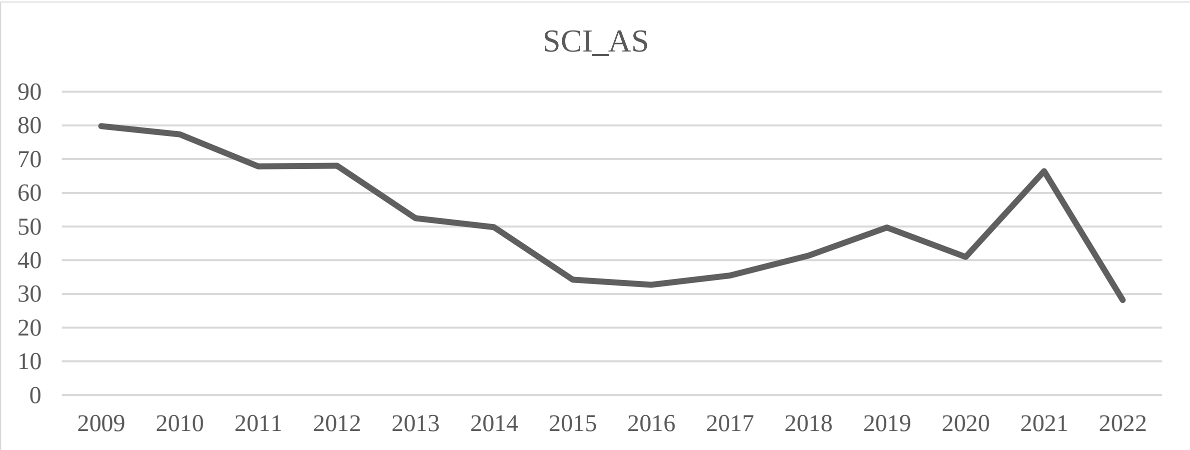


Figure 2: Trend of SCI_AS



SCI_AS has a higher variation coefficient than SCI_VA and SCI_FN, indicating greater variability in sector concentration when measured by asset size. As shown in Figure 2, the downward trend in sectoral credit concentration in terms of asset size (SCI_AS) continued until 2016, reaching a value of 32.71, before reversing into an upward trend after 2016, with its highest levels recently recorded in 2021 (66.47) and 2019 (49.74). While the highest SCI_AS figure was observed in 2009 (79.79), the minimum level occurred in 2022 (28.19).

The real sector's mean interest coverage ratio is positive (1.57) but weak in covering interest expenses and shows substantial variability, ranging from -3.30 to 10.09 among the observed entities.

Table 3. Correlation Coefficients between Independent Variables

Variable	SCI_AS	SCI_VA	SCI_FN
SCI_AS	1		
SCI_VA	0.72***	1	
SCI_FN	0.28***	-0.36***	1
INTC	0.21***	0.17***	0.11*

Note: SCI_AS: Sector Concentration Index based on sector's asset size. SCI_VA: Sector Concentration Index in terms of value added. SCI_FN: Sector Concentration Index in terms of firm number. INTC: Interest coverage ratio. *, ** and *** indicate 10%, 5% and %1 significance level.

Table 4. Sectoral Credit Distribution and Deviations

Sectors	$\mu(W_t)$	$\mu(\bar{W}_{t\_AS})$	$\mu(W_t - \bar{W}_{t\_AS})$	$\mu(W_t - \bar{W}_{t\_AS})^2$	$W_{2021} - \bar{W}_{2021\_AS}$	$(W_{2021} - \bar{W}_{2021\_AS})^2$
	μ(CS)	μ(AS)	μ(CS-AS)	μ(CS-AS)²	CS_{2021}- AS_{2021}	$(CS_{2021}- AS_{2021})^2$
Agriculture	0.49	0.56	-0.07	0.01	-0.15	0.02
Mining	1.22	1.80	-0.58	0.35	-0.59	0.34
Manufacturing	31.50	27.19	**4.30**	**21.24**	**1.25**	**1.57**
Electric	8.87	7.61	**1.26**	**3.33**	**2.78**	**7.75**
Water	0.20	0.24	-0.05	0.00	-0.09	0.01
Construction	13.37	13.82	-0.45	0.51	-0.43	0.18
Trade	21.17	22.18	**-1.01**	**7.84**	**-6.33**	**40.11**
Transport	6.39	6.40	**-0.01**	**2.51**	**3.39**	**11.47**
Accommodation	3.48	2.79	0.68	0.61	**1.39**	**1.92**
Information	2.40	3.30	-0.90	0.96	-0.73	0.53
Real estate	2.34	1.98	0.36	0.20	0.97	0.94
Professional	5.53	9.08	**-3.54**	**14.30**	-1.07	1.15
Administrative	1.88	1.61	0.27	0.10	-0.03	0.00
Education	0.23	0.39	-0.16	0.03	-0.18	0.03
Human health	0.70	0.74	-0.04	0.00	-0.12	0.02
Arts	0.18	0.20	-0.02	0.00	-0.02	0.00
Other service	0.06	0.10	-0.04	0.00	-0.03	0.00

Note: The first section under the sector names in Table 4 represents the 14-year average of sectoral credit distribution, while the second section, comprising the last two columns, shows the credit distribution for the selected year, 2021. μ represents the 14-year average. W_t denotes the share of the respective sector's credit risk (CS) within the real sector's total credit risk. $\bar{W}_{t\_AS}$ is the share of the sector's asset size (AS) into real sector total asset size, as the optimal credit allocation benchmark. W_{2021} denotes the sector's credit share for the year 2021 (CS_{2021}). $\bar{W}_{2021\_AS}$ is the ratio of the sector's asset size (AS) to the real sector's asset size for 2021 (AS_{2021}). Agriculture: agriculture, forestry and fishing. Mining: mining and quarrying. Electric: Electricity, gas, steam and air conditioning supply. Water: Water supply, sewerage, waste management and remediation activities. Trade: Wholesale and retail trade; repair of motor vehicles and motorcycles. Transport: Transport and storage. Accommodation: Accommodation and food service activities. Information: Information and communication. Real estate: Real estate activities. Professional: Professional, scientific and technical activities. Administrative: Administrative and support service activities. Human health: Human health and social work activities. Arts: Arts, entertainment and recreation. Other service: Other service activities

The correlations in Table 3 show that the Sector Concentration Index variables (SCI_AS, SCI_VA, SCI_FN) are positively correlated with each other to varying degrees. This indicate that sectors with a high concentration in one aspect tend to have high concentration in other aspects as well. However, SCI_VA and SCI_FN are negatively correlated, suggesting that sectors with a high concentration in terms of firm number tend to have lower concentration in terms of value added. The INTC variable exhibits relatively weaker positive correlations with the SCI variables.

Table 4 provides the distribution of sectoral credit risk within the real sector and, the deviation and squared deviation of the sector's credit share from the optimal credit share based on asset size, on average over 14 years and for the specific year 2021. According to the SCI_AS and SCI_FN indices for 2021, and as also seen in Figure 2 including SCI_AS indices, the real sector experienced the highest sectoral credit concentration in 2021. Therefore, sector credit distribution values in 2021 are also included in Table 3 as the second section.

According to the first section of Table 4 presenting the 14-year averages of sectoral credit distribution and deviations with the assumption of asset size as ideal distribution, there has been an increase in credit towards the manufacturing and electric (electricity, gas, steam and air conditioning supply) sectors, while credit allocation has decreased towards the professional (professional, scientific and technical activities), trade (wholesale and retail trade), and transport (transport and storage) sectors, respectively. In other words, banks have directed the loans they cut from the professional, trade and transportation sectors to the manufacturing sector. The disproportionately high allocation of credit towards manufacturing firms and, the disproportionately low allocation to the other three sectors (professional, trade, and transport) seem to be influential in the last 14 years sectoral credit concentrations.

The second section of Table 4, comprising the last two columns, shows the extent to which sectors' credit shares deviate from the optimal share (based on assumed asset size) for the year 2021. Similar to the previous section, when examining the top five sectors with the highest deviation, it is evident that credit usage has increased in the transport, electric, accommodation (accommodation and food service activities), and manufacturing sectors, respectively, while there has been a significant decrease in credit usage in the trade sector. This decline in the trade sector's credit share has played a key role in shaping credit sector concentration in 2021.

3.3. Method, Findings and Discussions

Panel data consisting of 17 sectors and 14 years were estimated using panel data analysis. According to the three ideal sector distribution assumptions three alternative sector concentration indices (SCI_AS, SCI_VA, SCI_FN) were calculated. Similarly, since there are three dependent variables (NPL_1, NPL_2, NPL_3) proxying credit risk, we estimated nine alternative regression specifications.

The general form of the panel data model (Baltagi, 2005p. 224; Tatoğlu, 2012p. 162) is shown with Equation (2), where Y represents the dependent variable, X′ represents the independent variable(s), and ε_{it} represents the error term. By adding the dependent and independent variables of this study to the general panel data model, 9 alternative equations were created and presented as Equations (3) through equations (10).

$$Y_{it} = \beta X'_{it} + \varepsilon_{it}, \quad (2)$$

$$NPL\_1_{i,t} = \beta\,(SCI\_AS_{i,t}) + \beta\,(INTC_{i,t}) + \varepsilon_{i,t}, \quad (3)$$

$$NPL\_1_{i,t} = \beta\,(SCI\_VA_{i,t}) + \beta\,(INTC_{i,t}) + \varepsilon_{i,t}, \quad (4)$$

$$NPL\_1_{i,t} = \beta\,(SCI\_FN_{i,t}) + \beta\,(INTC_{i,t}) + \varepsilon_{i,t}, \quad (5)$$

$$NPL\_2_{i,t} = \beta\,(SCI\_AS_{i,t}) + \beta\,(INTC_{i,t}) + \varepsilon_{i,t}, \quad (6)$$

$$NPL\_2_{i,t} = \beta\,(SCI\_VA_{i,t}) + \beta\,(INTC_{i,t}) + \varepsilon_{i,t}, \quad (7)$$

$$NPL\_2_{i,t} = \beta\,(SCI\_FN_{i,t}) + \beta\,(INTC_{i,t}) + \varepsilon_{i,t}, \quad (8)$$

$$NPL\_3_{i,t} = \beta\,(SCI\_AS_{i,t}) + \beta\,(INTC_{i,t}) + \varepsilon_{i,t}, \quad (9)$$

$$NPL\_3_{i,t} = \beta\,(SCI\_VA_{i,t}) + \beta\,(INTC_{i,t}) + \varepsilon_{i,t}, \quad (10)$$

$$NPL\_3_{i,t} = \beta\,(SCI\_FN_{i,t}) + \beta\,(INTC_{i,t}) + \varepsilon_{i,t}, \quad (11)$$

In Equations (3) to (11);

$NPL\_1_{i,t}$: Banking Sector Non-Performing Loans/Total Cash Loans.

$NPL\_2_{i,t}$: Banking Sector Non-Performing Loans (Gross)/Total Cash Loans.

$NPL\_3_{i,t}$: Real Sector Bad Debts/Cash and Non-Cash Credits.

$SCI\_AS_{i,t}$: Sector Concentration Index based on the sector's asset size (AS).

$SCI\_VA_{i,t}$: Sector Concentration Index based on the sector's value added (VA).

$SCI\_FN_{i,t}$: Sector Concentration Index based on the sector's firm number (FN).

$INTC_{i,t}$: Interest coverage ratio

Table 5 presents the results of tests aimed at determining appropriate estimators for the nine panel data models.

Table 5. Preliminary Test Results for Panel Model Determination

Model / Test			F Test	LR Test	LM Test	ALM Test	Score Test	Hausman Test
1	NPL_1 / SCI_AS	Statistics	0.38	0	6.54**	38.32***	0	6.52*
		P-Value	0.9857	1.0000	0.0106	0.0000	1.0000	0.0516
		Decision	Pooled	Pooled	Random	Random	Pooled	Fixed
2	NPL_1 / SCI_VA	Statistics	0.17	0	7.9***	40.99***	0	2.6
		P-Value	0.9999	1.0000	0.0049	0.0000	1.0000	0.2731
		Decision	Pooled	Pooled	Random	Random	Pooled	Random
3	NPL_1 / SCI_FN	Statistics	0.12	0	8.20***	35.47***	0	1.9
		P-Value	1.0000	1.0000	0.0042	0.0000	1.0000	0.3873
		Decision	Pooled	Pooled	Random	Random	Pooled	Random
4	NPL_2 / SCI_AS	Statistics	0.39	0	6.50**	38.45***	0	6.03**
		P-Value	0.9843	1.0000	0.0108	0.0000	1.0000	0.0489
		Decision	Pooled	Pooled	Random	Random	Pooled	Fixed
5	NPL_2 / SCI_VA	Statistics	0.17	0	7.87***	41.11***	0	2.67
		P-Value	0.9999	1.0000	0.0050	0.0000	1.0000	0.2633
		Decision	Pooled	Pooled	Random	Random	Pooled	Random
6	NPL_2 / SCI_FN	Statistics	0.12	0	8.21***	35.73***	0	1.88
		P-Value	1.0000	1.0000	0.0042	0.0000	1.0000	0.3898
		Decision	Pooled	Pooled	Random	Random	Pooled	Random
7	NPL_3 / SCI_AS	Statistics	0.18	0	7.83***	45.78***	0	0.47
		P-Value	0.9998	1.0000	0.0051	0.0000	1.0000	0.7895
		Decision	Pooled	Pooled	Random	Random	Pooled	Random
8	NPL_3 / SCI_VA	Statistics	0.03	0	8.91***	38.98***	0	2.67
		P-Value	1.0000	1.0000	0.0028	0.0000	1.0000	0.2633
		Decision	Pooled	Pooled	Random	Random	Pooled	Random
9	NPL_3 / SCI_FN	Statistics	0.33	0	6.79***	29.36***	0	5.03*
		P-Value	0.9940	1.0000	0.0092	0.0000	1.0000	0.0807
		Decision	Pooled	Pooled	Random	Random	Pooled	Fixed

Note: NLP_1: Banking Sector Non-Performing Loans/Total Cash Loans. NPL_2: Banking Sector Non-Performing Loans (Gross) / Total Cash Loans. NPL_3: Real Sector Bad Debts/Cash and Non-Cash Credits. SCI_AS_{it}: Sector Concentration Index in terms of the sector's asset size. SCI_VA_{it}: Sector Concentration Index in terms of value added. SCI_FN_{it}: Sector Concentration Index in terms of firm number. $INTC_{it}$: Interest coverage ratio. *, ** and *** indicate 10%, 5% and %1 significance level.

Despite a few Hausman test results favoring the fixed effects estimator, taking into account the data characteristics, the nine models given in Equations (3) to (11) are estimated using a fixed effects estimator, and the parameters of the nine regressions are presented in Tables 6.

Table 6. Parameters of Estimations with Fixed Effects Estimator

Dependent Variables	**NPL_1**		**NPL_2**		**NPL_3**	
Explanatory Variables	**Coeff.**	**t-sta.**	**Coeff.**	**t-sta.**	**Coeff.**	**t-sta.**
SCI_AS	0.02***	(14.13)	0.02***	(14.23)	0.01***	(6.28)
INTC	-0.22***	(-4.73)	-0.21***	(-4.70)	-0.12***	(-4.05)
F / X² statistics	81***		101***		23***	
SCI_VA	0.001***	(12.77)	0.001***	(13.05)	-0.001***	(-28.28)
INTC	-0.153***	(-3.80)	-0.14***	(-3.79)	-0.05*	(-1.86)
F / X² statistics	81***		85***		772***	
SCI_FN	0.002***	(10.62)	0.002***	(10.27)	0.004***	(22.53)
INTC	-0.13**	(-2.26)	-0.12**	(-2.23)	-0.15***	(-3.58)
F / X² statistics	154***		143***		315***	

Note: Table 6 presents statistics for 9 panel data models applied fixed effects estimator with robust standard errors. Panel data consists of 17 sectors and 14 years. The first row includes three dependent variables. NLP_1: Banking Sector Non-Performing Loans/Total Cash Loans. NPL_2: Banking Sector Non-Performing Loans(Gross)/Total Cash Loans. NPL_3: Real Sector Bad Debts/Cash and Non-Cash Credits. The first column refers to the three independent variables. SCI_AS: Sector Concentration Index in terms of the sector's asset size. SCI_VA: Sector Concentration Index in terms of value added. SCI_FN: Sector Concentration Index in terms of firm number. INTC: Interest coverage ratio. Coef.: coefficient. Sta.: statistics. *, ** and *** indicate 10%, 5% and %1 significance levels, respectively.

The results presented in Table 6 provide insights into the regression parameters with three alternative dependent variables (NPL_1, NPL_2, NPL_3) and three different sector concentration indices (SCI_AS, SCI_VA, SCI_FN) across nine model specifications. The second column of Table 6 shows the coefficients for the effect of the SCI variables on NPL_1. In the model assessing the relationship between NPL_1 and SCI_AS, the coefficients for SCI_AS are statistically significant, indicating a positive correlation between sectoral credit concentration based on asset size and the ratio of non-performing loans to total cash loans in the banking sector. Although this result is statistically significant, the coefficient of SCI_AS is 0.03, implying that a 10% increase in the sector concentration index corresponds to a 0.2% rise in NPL_1. While a 0.2% increase may not seem substantial on its own, it could represent a significant amount depending on the total loan portfolio size of the banking sector and may contribute to financial stability concerns.

In the same model, the strong negative relationship between interest coverage and the NPL_1 ratio suggests that higher interest coverage leads to a reduction in non-performing loans. For NPL_1, the INTC coefficient is -0.22, indicating that an increase in the interest coverage ratio by 1 unit results in a 0.22% decrease in the non-performing loans ratio. Economically, this implies that firms with a better ability to cover interest payments are likely to experience lower default rates, thereby enhancing the credit quality and overall health of the banking system. Similar patterns are observed in the regression models examining NPL_1 concerning SCI_VA and SCI_FN. In both cases, the coefficients for the respective SCI variables are statistically significant, indicating a positive relationship between sectoral credit concentration in terms of value added or firm number and the NPL_1 ratio. Additionally, the coefficients for INTC remain statistically significant and negative in these models as well.

The third column of Table 6 presents the results of regressions with NPL_2 as the dependent variable, representing banking sector non-performing loans (gross) as a ratio to total cash loans. The parameters of the three models confirm the positive effect of sectoral credit concentration indices on the second alternative NPL rate. Specifically, the coefficients for SCI_AS (0.02) suggest that greater concentration may lead to increased risk exposure within the banking sector. The INTC variable still has an economically and statistically significant negative effect on NPL_2. The strong coefficients for INTC demonstrate that improvements in firms' ability to cover interest payments are linked to lower levels of non-performing loans and better asset quality in the banking sector.

The last column of Table 6 presents the parameters of regressions where the dependent variable is NPL_3, representing the ratio of real sector bad debts to cash and non-cash credits. The models that include the SCI_AS and SCI_FN concentration indices provide evidence that sectoral credit concentration amplifies bad debt rates within the real sector. In contrast, models regressing SCI_VA against the bad debt ratio reveal a significant negative relationship. Additionally, a higher INTC remains a crucial factor in mitigating the default rate within the real sector. The coefficients for SCI_AS (0.01) and SCI_FN (0.004) indicate a positive association with bad debts; however, the economic significance may be limited due to the small magnitude of these coefficients. Conversely, the strong negative coefficients for INTC consistently demonstrate that higher interest coverage is linked to lower bad debt rates, reinforcing the importance of firms' ability to meet their interest obligations in reducing defaults in the real sector.

When we combine all results from the nine models in Table 6, we can infer that higher sectoral credit concentration in real sector credits, as measured by different sector concentration indices, is associated with increased credit risk levels measured by both banking sector non-performing loan data and real sector bad debts data. Diversification compatible with the sectors’ asset size is more effective in reducing credit risk. The negative relationships of INTC imply that sectors characterized by lower interest coverage ratios are more prone to having higher non-performing or bad debt ratios.

Overall, the positive coefficients for the SCI variables underscore the potential risks associated with sectoral concentration. Credit default risk is more sensitive to a diversified loan portfolio in line with asset size. The consistently negative and strong coefficients for INTC highlight the critical role of interest coverage in maintaining financial health and reducing non-performing loans.

The results correspond with the six studies included in this research—three based on Turkish data and three from other countries—that directly focus on credit risk and sectoral loan diversification. Notably, studies such as Bebczuk and Galindo (2008), using data from Argentina's major firms and bank debt data, Chen et al. (2013) on 16 commercial banks in China, and Beck and De Jonghe (2013) in an international context, demonstrate the increasing impact of sectoral concentration on credit risk. Furthermore, three (Tunay, 2015; Sarı, 2019; Yalçın & Tunay, 2020) of the five Turkish studies that directly examine the relationship between sectoral credit concentration and credit risk conclude that diversification in loan portfolios reduces credit risk.

A robustness test was conducted using system GMM estimations that included the one-lagged value of the related NPL variable as the first regressor in each model specification. According to the findings of system GMM presented in Table 7, concentration indexes positively impact NPL rates, with the SCI_AS index (based on asset size) having the strongest effect. One-period lagged NPLs are statistically significant across all models. INTC variable is negatively correlated in 5 out of 9 models at 10% and 5% significance levels.

Table 7. The Parameters of Estimations with System GMM

Dependent Variables	**NPL_1**		**NPL_2**		**NPL_3**	
Explanatory Variables	**Coeff.**	**z-sta.**	**Coeff.**	**z-sta.**	**Coeff.**	**z-sta.**
L_NPL	0.64***	94.85	0.64***	98.18	0.53***	99.04
SCI_AS	0.02***	23.72	0.02***	24.41	0.02***	34.56
INTC	-0.05*	-1.67	-0.05*	-1.67	-0.03	-1.53
P_Hansen	0.001		0.001		0.001	
P_Diff. in Hansen	0.7776		0.789		0.737	
L_NPL	0.73***	83.24	0.73***	83.92	0.66***	103.31
SCI_VA	0.001***	12.99	0.001***	13.21	0.001***	23.18
INTC	-0.06*	-1.94	-0.06**	-1.97	-0.03	-1.49
P_Hansen	0.001		0.001		0.001	
P_Diff. in Hansen	0.637		0.639		0.915	
L_NPL	0.51***	14.39	0.53***	15.10	0.09***	3.30
SCI_FN	0.003***	8.54	0.003***	8.13	0.004***	18.75
INTC	-0.08	-1.61	-0.07	-1.60	-0.06*	-1.76
P_Hansen	0.001		0.001		0.001	
P_Diff. in Hansen	0.835		0.848		0.712	

Note: Table 7 presents statistics of system GMM estimations with robust standard errors for 9 panel models. The observation number in each model is 221. L_NPL reflects the one-lagged value of the related NPL variable. L_NPL enters all regressions as the first regressor. P_Hansen and P_ Difference-in-Hansen are p-values for exogeneity tests. Coef.: coefficient. Sta.: statistics. *, ** and *** indicate 10%, 5% and %1 significance.

4. CONCLUSION

This study highlights the significant risks posed by sectoral concentration in bank loans, which increases susceptibility to credit risk and contagion within the financial system. Analyzing data from the Turkish real and banking sectors from 2009 to 2022, we distinguish our research by utilizing the Sector Concentration Index (SCI) alongside a comprehensive dataset. The SCI aligns with optimal diversification strategies in portfolio theory, allowing for a more meaningful comparison between the sectoral distribution of bank loans and the market's ideal distribution, as a corrected form of the commonly used Herfindahl-Hirschman Index (HHI). Unlike previous studies that primarily relied on bank-level data, our analysis integrates both sectoral and bank-level data.

Our set data evaluation indicates a disproportionately high allocation of credit to manufacturing firms, while other sectors, such as professional services, trade, and transport, receive comparatively less.

This allocation has significantly influenced sectoral credit concentrations over the past 14 years. The panel data analysis reveals a positive correlation between sectoral credit concentration, measured by various indices, and non-performing loan (NPL) rates in the banking sector, as well as bad debt rates in the real sector. Among the three concentration indexes examined, the one based on asset size demonstrates the strongest effect on NPLs, suggesting that diversification according to asset volume can more effectively mitigate credit risk. Furthermore, operating within sectors characterized by low-interest coverage ratios exacerbates credit risk. This finding underscores the importance of sector-specific financial health in managing default rates and ensuring adequate interest coverage to reduce credit risk in the real economy.

Overall, sectoral concentration in real sector credits contributes to heightened credit risk, manifesting as non-performing loans in the banking sector and bad debt in the real sector. This outcome emphasizes the benefits of diversification in reducing credit risk, aligning with economic theory, portfolio management principles, and financial intermediation theory, which assert that insufficient diversification increases vulnerability to credit risk.

These findings provide valuable insights into the complex relationship between sectoral concentration and credit risk. Given the financial and economic implications, targeted policy recommendations are essential. Based on these findings, it is recommended to implement policies that encourage diversification in lending practices, particularly by promoting loan allocation proportional to asset size. Additionally, policies should focus on enhancing the monitoring and supervision of sectoral credit concentration.

One possible avenue for further research is to distinguish the determinants of sectoral credit concentration, which could contribute to developing more effective risk management strategies and maintaining financial stability, potentially expanding the generalizability of these findings.

The study does not necessitate Ethics Committee permission.

The study has been crafted in adherence to the principles of research and publication ethics.

The authors declare that there exists no financial conflict of interest involving any institution, organization, or individual(s) associated with the article. Furthermore, there are no conflicts of interest among the authors themselves.

The authors contributed equally to the entire process of the research.

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