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Original Research Article

The Impact of Large Loan Credit Concentration Risk on Default Rates: Empirical Evidence from Banks Listed on Tehran Stock Exchange

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Bank facilities can be categorized into large-scale and non-large-scale facilities based on their value and in compliance with banking regulations. Given the significant share of large-scale facilities in the country's total credit portfolio, the exposure to a limited number of borrowers—primarily major corporations—and their subsequent direct and indirect effects on the banking system and the economy, this paper investigates the credit concentration risk associated with large-scale facilities.

Using the Herfindahl-Hirschman Index (HHI), the degree of name concentration in the allocation of large-scale facilities among beneficiaries was measured, and its impact on the default rate of these facilities was estimated using a Generalized Method of Moments (GMM) model for 15 banks listed on the Tehran Stock Exchange during the period 2022 to 2024. Additionally, the share of large-scale facilities in the total loans granted by each bank (as another concentration measure) was included in the model, along with the loans-to-deposits ratio and the capital adequacy ratio as control variables. The model results indicate strong persistence and a statistically significant impact of the lagged default rate of large-scale facilities. We find that name concentration in the allocation of large-scale facilities has a negative effect on the default rate of these facilities. However, the share of large-scale facilities in total loans—as an alternative concentration measure—did not exhibit a statistically significant effect on their default rate. Furthermore, the loans-to-deposits ratio, which serves as an indicator of banks' liquidity and resource management performance, had a significant negative effect. Additionally, an improvement in the capital adequacy ratio led to a statistically significant reduction in the default rate of large-scale facilities.

Keywords: Risk management, Large corporate loans, Credit risk, Name concentration risk, Loan default rate

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JEL Classification: G28, G23, G22, C15

1 Introduction

Given the dominance of a bank-based financial system in Iran's resource mobilization and allocation framework, the identification, assessment, and management of banking risks have consistently held a prominent position in both regulatory priorities and economic research agendas. One critical aspect of bank risk management is the management of loan portfolios, which holds particular significance not only due to its impact on a bank's stability and operational efficiency but also because of the direct and multilateral linkages between banking performance and economic sectors, as well as other components of the financial system.

One of the components affecting the risk management of banks' credit portfolios is concentration risk. Concentration risk can be defined as "any single exposure or group of exposures with the potential to produce losses large enough (relative to a bank's capital, total assets, or overall risk level) to threaten a bank's health or ability to maintain its core operations" (Hibbeln, 2010). Concentration may occur in credits, assets, deposits, markets, or a bank's operational practices. Therefore, concentration risk itself constitutes a subset of all liquidity, market, operational, and credit risks.

Specifically, to measure credit concentration risk, it is necessary to classify the credit portfolio into two categories - granular vs non- granular portfolios - based on the size of the portfolio and the size of individual credits. Based on this classification, the share of large exposures, which is one of the recognized manifestations of concentration, is determined. In Basel regulations, credit concentration risk arising from large exposures has been implicitly addressed through establishing regulations for granting large exposures and considering the impact of such exposures on bank capital requirements and credit risk measurement of the credit portfolio. These regulations mainly focus on risks stemming from large facilities and exposures to related parties or entities, commonly referred to name concentration.

In the Islamic Republic of Iran, the Money and Credit Council, in implementation of Clause (4) of Article (34) of the Country's Monetary and Banking Law and Article (44) of the same law and also based on Item (1) of Clause (d) of Article 97 of the Fifth Five-Year Development Plan Law of the Islamic Republic of Iran, has addressed the issue of concentration in large-scale credits. Accordingly, the Large-Scale Facilities and Commitments Regulation was approved to facilitate the allocation of banking resources to a larger number of individuals in society, further diversify the credit portfolio of credit institutions, and minimize losses resulting from the concentration of banking resources (CBI, 2004). The mentioned regulation has defined single

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beneficiary, large-scale facilities and commitments in the country and specifies the requirements of credit ceiling limits, internal controls and information reporting obligations for it. Through Note 16 of the 1401 Annual Budget Law, new requirements were added to these regulations.

Despite significant regulatory attention given to establishing large exposure regulations and their incorporation into bank capital requirements and credit risk calculations, limited empirical research has addressed this area in the domestic context. Based on theoretical and empirical needs assessment in this field, the present study focuses on the issue of name concentration in large exposures among banks listed on the Tehran Stock Exchange and empirically examines its relationship with credit risk (specifically the default rate of large exposures). However, it is crucial to acknowledge that our empirical investigation is constrained by data limitations, particularly the short time series available (2022-2024) and potential identification errors in single beneficiaries, which necessitate cautious interpretation of the results.

While traditional banking theory suggests that banks should diversify their loan portfolios to reduce credit risk, corporate finance theory alongside some empirical and theoretical studies (such as Winton, 1999 and Acharya et al., 2006) in certain cases emphasize the benefits of credit concentration. They argue that solely recommending diversification without considering bank-specific characteristics like capital and risk levels may have adverse effects on bank performance.

The present article, through empirical examination of available data on related-party large borrowers in Iran, seeks to investigate whether a statistically significant relationship can be found between concentration measures and the default rate of large exposures. Although precise answers to this question remain constrained by data limitations, this study represents a meaningful effort to advance the discussion of concentration in the domestic banking literature.

Accordingly, this study measures the name concentration index in large exposures within the Iranian banking system and examines the impact of credit distribution among related parties on the default rate of large exposures, employing a panel System GMM. Furthermore, the ratio of large exposures to total credit for each bank is utilized as a metric to assess how credit allocation between wholesale and retail segments affects the default rate of large exposures. Additionally, the loan-to-deposit ratio and capital adequacy ratio of banks are incorporated as control variables.

Accordingly, in the subsequent sections of this paper, Section 2 reviews the theoretical foundations of the impact of concentration on loan default rates

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and Section 3 reviews some prior studies in this field. Section 4 introduces the empirical model and its variables. Section 5 presents the hypothesis tests and outputs of the empirical model. Finally, Section 6 provides the summary and conclusions.

2 Theoretical Foundation: An Integrated View of Risk, Concentration, and Banking

2.1 The Role of Banks and the Imperative of Risk Management

Financial intermediation theories highlight intermediaries' cost advantages 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 (Şahin & Acar, 2024). Bank monitoring contributes to maintaining financial system stability and soundness by reducing risks for depositors and other creditors. Within this framework, two monitoring approaches emerge: rule-based regulatory monitoring (often termed compliance monitoring), and risk-based monitoring.

Following the 2008 crisis, many regulatory authorities have more rigorously adopted risk-based supervision for monitoring the banking system. Whereas rules-based supervision focuses on issuing regulations and overseeing their implementation across the banking network, the risk-based supervisory system primarily concentrates on identifying sources of risks that significantly impact banks. It also evaluates the quality of risk management and internal controls. The risk analysis, the quantity and quality of the bank risk management is the fundamental base for the activities of supervisory authorities. Based on the analysis, they obtain a comprehensive picture of the risk profile of the banking institutions. The risk profile of banks provides a basis for determining the supervisory strategy, planning the supervisory cycle, and initiating corrective measures in the banking institutions (Delova-Jolevska & Andovski, 2013).

Within this framework, risk identification constitutes the first step in risk management. Risk is a multi-faceted and difficult concept to define. Usually, it means a state of uncertainty and danger resulting from the probable occurrence of an event which is independent of the one affected. Therefore, risk can be defined as a condition or event that could lead to financial loss (Kozak, 2015).

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Generally, based on a theoretical literature perspective, the risks faced by intermediary markets can be categorized into three groups:

- Portfolio risks (such as market risk, counterparty credit risk, financial risk, liquidity risk, mismatch risk, etc.),
- Corporate risks (including operational risk, managerial risk, compliance risk, financial risk, legal risk, strategic risk, related-party risk and contagion, etc.),
- Systematic risks (comprising negative spillover effects risk from other institutions and economic recession risk) (IOSCO, 2009).

Banks as financial intermediaries play a central role in an economy by mobilizing savings, reducing costs of financial transactions and managing risks. Careful management of banks' credit portfolios is essential for their stability because a significant amount of bank revenue is from interest income generated from lending. The financial crises of 2007/2008 emphasized the need for banks to actively measure and control their credit exposures to ensure minimal credit risk of loan portfolios (Adzobu et al., 2017).

Credit risk can be defined as 'the potential that a contractual party will fail to meet its obligations in accordance with the agreed terms'. Credit risk is also variously referred to as default risk, performance risk or counterparty risk. These all fundamentally refer to the same thing: the impact of credit effects on a firm's transactions. There are three characteristics that define credit risk: 1. Exposure (to a party that may possibly default or suffer an adverse change in its ability to perform). 2. The likelihood that this party will default on its obligations (the default probability). 3. The recovery rate (that is, how much can be retrieved if a default takes place) (Brown & Moles, 2014).

Non-performing loans (NPLs) are the most commonly used metric for assessing credit risk. This indicator reflects the risk that underlying cash flows from loans held by financial institutions may not be fully repaid and is related to the quality of bank assets. Numerous earlier empirical investigations demonstrate that bank failure is typically caused by a high amount of NPLs (Alnabulsi et al., 2023).

The high level of non-performing loans is widely recognized as a relevant indicator of the banks' asset quality, and it directly affects the overall financial performance of the whole banking sector. The level of non-performing loans provides an important signal of potential future losses for the banking system and can be used to mark the onset of a financial crisis (Ferreira, 2022).

Exploring the determinant factors of ex-post credit risk is an issue of substantial importance for regulatory authorities concerned about financial stability and banks' management. The ex-post credit risk takes the form of

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non-performing loans (NPLs) (Louzis et al., 2012). Existing literature on credit risk determinants has identified a broad spectrum of key factors, including bank-specific factors, banking industry-specific factors, and macroeconomic variables (Alnabulsi, 2023).

The primary objective of this study is to analyze the impact of credit portfolio concentration in large exposures on the NPL ratio of this category of loans, which falls under bank-specific factors. Although mandated large exposures may exogenously influence credit portfolio distribution, credit allocation among customers is fundamentally an endogenous organizational variable, dependent on managerial objectives, institutional formation, and operational execution variables.

2.2 Credit Concentration Risk: Synthesizing Divergent Theoretical Views

Concentration risk can be defined as "any single exposure or group of exposures with the potential to produce losses large enough (relative to a bank's capital, total assets, or overall risk level) to threaten a bank's health or ability to maintain its core operations" (Hibbeln, 2010). This definition, while focusing on the negative tail risk, inherently acknowledges that concentration is a source of potential volatility, which can have both positive and negative outcomes depending on the bank's ability to manage it.

Financial institutions' credit portfolios are subject to several forms of concentration. Concentrations in terms of size or number of credits and concentrations in sectors are well recognized forms of the risk. The risk measurement of financial institutions' credit portfolios requires the consideration of concentration as one aspect of credit risk (Nokkala, 2025). Hibbeln (2010) classifies concentration into three types: Name concentration, Sectoral concentration (industry and geographic concentration), and Credit contagion. According to the Bank for International Settlements (BIS, 2004), size-related concentration risk comprises two subtypes: Single-name concentration (when one counterparty is disproportionately large relative to others), and Portfolio name concentration (when the number of counterparties is small relative to portfolio size).

The academic literature presents a seeming paradox regarding the effect of concentration on bank risk and performance, which this study seeks to address within the Iranian context.

The Diversification Imperative (Traditional View): Traditional banking theory, aligned with Modern Portfolio Theory (Markowitz, 1959), suggests that banks should diversify their loan portfolios to reduce credit risks.

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According to the theory of asymmetric information (e.g., Boot, 2000), Diamond (1984) argues that diversification allows banks to transform monitored debt into unmonitored debt, reducing vulnerability to sector-specific downturns. This view posits that increased diversification leads to lower future provisions and a reduction in realized risks (Le & Diep, 2020).

The Specialization Advantage (Corporate Finance View): In contrast, corporate finance theory emphasizes the benefits of credit concentration in specific cases. It states that firms should specialize to enjoy the comparative advantage of developing expertise (Jensen, 1986; Denis et al., 1997). Banks, by specializing in a few sectors, develop superior screening and monitoring abilities, which reduce adverse selection, allow for better collateral assessment, and enable early detection of borrower deterioration, thereby mitigating risk (Adzobu et al., 2017).

2.3 Winton's (1999) Contingency Theory: A Theoretical Synthesis

The apparent contradiction between these views is resolved by the theoretical model of Winton (1999), which provides a critical integrative framework for this study. Winton's model moves beyond a generic prescription for or against concentration, arguing that the relationship is non-linear and contingent on bank-specific factors, most notably the bank's underlying risk profile and monitoring capabilities.

The essence of Winton's model lies in understanding the endogenous nature of bank credit portfolio quality: it is partly determined by monitoring levels, which themselves are influenced by changes in the bank's credit portfolio concentration or diversification. This creates a feedback loop: a bank's existing risk level determines the effectiveness of its monitoring, which in turn influences whether diversification or concentration will be more beneficial for future risk outcomes.

Based on this framework, he theoretically examines two hypotheses that are highly relevant to the Iranian banking context characterized by high existing NPLs and capital adequacy challenges:

The Non-Linear Hypothesis: The relationship between bank returns and risk diversification is inverse U-shaped. A bank gains maximum benefit from economic sector diversification when it has moderate default risk. However, if the bank faces high credit risk, diversification may actually increase its probability of failure by diluting its monitoring efforts and exposing it to new sectors where it lacks expertise (Acharya et al., 2006).

The Monitoring Dilution Hypothesis: A bank's monitoring effectiveness may be lower in newly entered and competitive sectors, leading to poorer loan

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quality through diversification. This occurs due to (a) a lack of monitoring expertise and associated learning costs, (b) adverse selection and the "winner's curse" in competitive markets, and (c) organizational inefficiencies that arise from increased size and complexity (Winton, 1999).

This analysis underscores that blanket policy recommendations are misguided. Instead, a balanced, case-specific approach is required, where banks and regulators must carefully weigh the potential benefits of diversification against the challenges of entering new and unfamiliar markets. The capital adequacy ratio and loan-to-deposit ratio, included as control variables in our model, serve as proxies for these bank-specific characteristics (e.g., inherent riskiness and resource management quality) that Winton's model identifies as crucial moderating factors.

Therefore, for the high-risk Iranian banks in our sample, Winton's model predicts that the monitoring advantages of specialization (the corporate finance view) may outweigh the traditional diversification benefits (the portfolio theory view). This leads to our core hypothesis that name concentration (HHI) will be associated with lower default rates for large exposures.

2.4 Regulatory Context and Large Exposures

Given the importance of the issue, capital is explicitly stipulated in banking regulations to cover future losses arising from credit concentration risk. Banking regulation has rules both on concentration risk and on large exposures (BCBS 2014). A rapidly growing literature, originating from the seminal contribution by Gabaix (2011), has emphasized the "granular" origins of macroeconomic outcomes, where shocks to large borrowers can affect aggregate fluctuations (Galaasen et al., 2020). Credit concentration risk on large credits in the Basel regulations is implicitly addressed through setting large exposure rules (Nokkala, 2022).

In Iran, the Large Facilities and Commitments Regulation, approved by the Supreme Money and Credit Council (CBI, 2004), defines a large exposure as any facility to a single beneficiary exceeding 20% of a bank's capital and caps the aggregate of such exposures at 800% of capital. The recent public disclosure of this data since 2022 provides a novel opportunity to test the theoretical framework outlined above. As shown in Figure 1, large facilities constitute a significant and growing share of the Iranian banking sector's credit portfolio, underscoring the practical relevance of this study.

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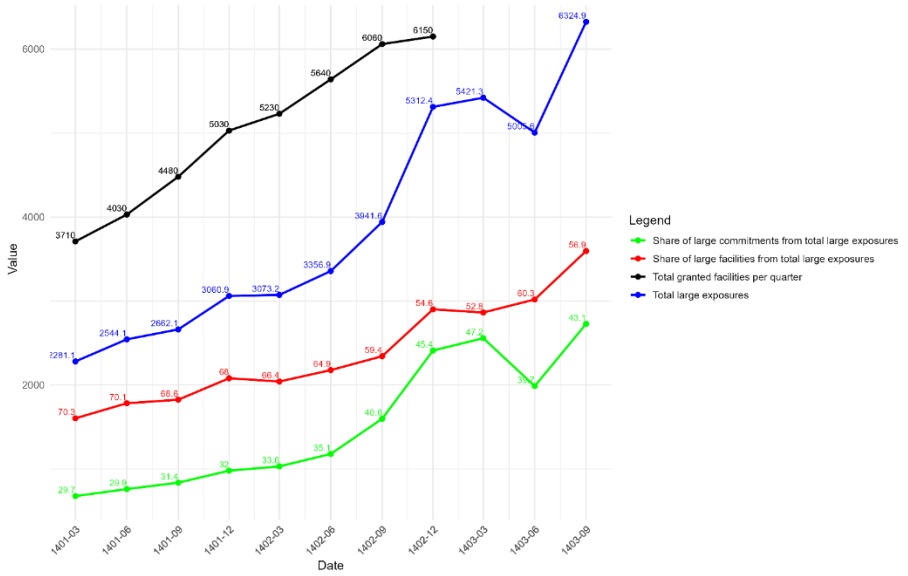

Figure 1. Position of Large Facilities and Commitments in the Banking Network (Values in 10 trillion Rials)
Source: Research Findings

This study examines concentration risk through two complementary metrics: (1) name concentration (using the Herfindahl-Hirschman Index) among large exposure beneficiaries, and (2) the share of large exposures in a bank's total loan portfolio. The analysis draws on official disclosure data, recognizing that these high-value exposures warrant particular risk management attention due to their disproportionate economic influence.

3 Literature Review

Empirical research on credit concentration presents a complex and often contradictory picture, reflecting the theoretical tension between diversification and specialization. Studies vary significantly based on their geographical context, methodological approach, and the specific type of concentration measured.

A strand of literature aligns with traditional portfolio theory, finding a positive relationship between diversification and stability. Chandramohan et al. (2022), studying Indian banks, found that functional, geographic, and credit portfolio diversification jointly enhanced bank stability. Similarly, Şahin &

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Acar (2024) concluded that sectoral concentration in Turkey increased credit risk, advocating for diversification.

Conversely, another body of work supports the specialization thesis, particularly in contexts where monitoring advantages outweigh diversification benefits. Tabak et al. (2011) discovered that concentration in Brazil led to higher returns and lower default risk, noting that the benefits diminish as a bank's inherent risk increases. This finding is crucial as it suggests a non-linear relationship. Supporting this, Behr et al. (2007) found that specialized German banks achieved higher returns and lower NPLs, though diversified banks exhibited more stable risk profiles.

The most nuanced findings, which build upon Winton's (1999) theoretical model, indicate that the effect is contingent on bank-specific factors. Acharya et al. (2006) provided pivotal empirical support for Winton, demonstrating that diversification's impact on Italian banks depended critically on their pre-existing risk level. For high-risk banks, diversification reduced returns and increased risk, while for low-risk banks, geographic diversification was beneficial. Huynh & Dang (2021) further refined this by showing that business models and market power in Vietnam act as significant moderating variables.

Methodologically, studies have evolved to address endogeneity concerns. While earlier studies like Raei et al. (2016) on the Tehran Stock Exchange used pooled regression, more recent research (e.g., Chandramohan et al., 2022; Huynh & Dang, 2021) employs dynamic panel models and the Generalized Method of Moments (GMM) to better establish causality. Furthermore, scholars have developed more sophisticated measures, such as the risk-adjusted HHI proposed by Chen et al. (2013), to better capture the systemic risk embedded in sectoral concentrations.

A critical gap addressed by Nokkala (2022) is the role of large exposures themselves, showing that their aggregation can have ambiguous effects on portfolio risk, contingent on the initial portfolio structure. This highlights the need to directly measure concentration within the large exposure segment itself, a gap this study aims to fill.

This study integrates itself into this contested literature by empirically testing Winton's contingency theory within the unique and high-risk context of the Iranian banking system. Unlike previous domestic studies (e.g., Raei et al., 2016), this research utilizes a more robust System-GMM estimator to address dynamic endogeneity. It moves beyond aggregate diversification measures by specifically investigating name concentration (HHI) within the large exposure portfolio a segment of critical regulatory and systemic importance. By examining how this specific concentration interacts with

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bank-specific factors (capital adequacy and the loan-to-deposit ratio), this study aims to provide nuanced, context-specific evidence on whether the monitoring advantages of concentration or the diversification benefits of risk-spreading prevail for Iranian banks.

4 Empirical Model and Research Variables

4.1 Econometric Framework and Estimation Methodology

Building upon the theoretical foundations outlined previously, this study aims to examine the impact of concentration levels in large exposures on the ratio of non-performing loans to total large exposures (referred to as the default rate of large exposures) using advanced panel data regression methods.

Panel data methods offer several distinct advantages for this type of analysis, including: (1) access to more informative data by combining cross-sectional and time-series dimensions; (2) higher degrees of freedom and improved efficiency of parameter estimates; (3) better capacity to control for unobserved heterogeneity; and (4) reduced multicollinearity among explanatory variables (Baltagi, 2013; Wooldridge, 2010). However, these methods also present well-documented limitations, including potential endogeneity issues, dynamic panel bias, and the need to carefully address fixed effects.

4.1.1 System GMM Estimation Rationale

In the present study, the System Generalized Method of Moments (System GMM) estimator with two-way fixed effects (time and individual) is employed. This choice is motivated by several critical considerations:

1) Dynamic Nature of Default Rates: Non-performing loans typically exhibit persistence over time, where current default rates are influenced by past values. The inclusion of a lagged dependent variable captures this dynamic adjustment process.
2) Endogeneity Concerns: Concentration measures (HHI and CON) may be endogenous due to reverse causality—banks with higher risk may deliberately adjust their concentration levels, while concentration itself affects risk.
3) Unobserved Heterogeneity: The model incorporates bank fixed effects to control for time-invariant unobserved bank characteristics and time fixed effects to capture common temporal shocks affecting all banks.

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4) Short Time Dimension: With only 5 semi-annual periods, System GMM provides more efficient estimates than alternative estimators for "small T, large N" panels (Roodman, 2009).

The general form of the empirical model is specified as follows:

$$+ {}_{tj}IHH_{\text{IHH.i}}\beta + {}_{1-tj}etar tlafed_{\text{gal.i}}\beta + {}_{\text{ti}}\alpha = {}_{tj}etar tlafed \quad (1)$$
$$\beta_{\text{i.CON}}CON_{jt-1} + \beta_{\text{i.LDR}}LDR_{jt-1} + \beta_{\text{i.CAR}}CAR_{jt-1} + \mu_t + \lambda_t + \varepsilon_{\text{it}}$$

In Equation (1), $defalt_rate_{jt-1}$and $defalt_rate_{jt-1}$ represent the default rate of large exposures in periods t and t-1 respectively, HHI_{jt} is the Herfindahl-Hirschman Index of large exposure distribution among single beneficiaries, CON_{jt-1} denotes the ratio of large exposures to total loans for bank j in period t-1, LDR_{jt} is the loan-to-deposit ratio of bank j at time t-1, and CAR_{jt} represents the capital adequacy ratio of bank j at time t-1. The model includes bank fixed effects (μ_t) and time fixed effects (λ_t) to control for unobserved heterogeneity and common temporal shocks.

4.1.2 Data Limitations and Sample Construction

The study utilizes semi-annual data from 2022 (1401 SH) to the first half of 2024 (1403 SH), comprising 5 time periods for 15 banks listed on the Tehran Stock Exchange. The relatively short time series constitutes a significant limitation, potentially affecting the robustness and generalizability of findings. However, the System GMM approach helps mitigate some concerns related to short time dimensions.

The sample includes: Eghtesad Novin Bank, Parsian Bank, Post Bank, Pasargad Bank, Tejarat Bank, Middle East Bank, Day Bank, Samatn Bank, Sina Bank, Saman Bank, Export Development Bank of Iran, Gardeshgari Bank, Mellat Bank, and Mellal Financial Institution.

4.2 Variable Definitions and Measurement

4.2.1 Dependent Variable: Large Exposure Default Rate

The dependent variable measures credit risk in large exposures using the ratio of non-performing large loans to total large exposures:

As theoretically explained, among the most famous and frequently used variables for measuring default probability that is known in literature as a credit risk indicator is the non-performing loans to total loans issued ratio. Thus the large exposures default rate is calculable from the following relation:

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$$defalt_rate_{jt} = \frac{NPL^{large}{}_{jt}}{D^{large}{}_{jt}} \quad (2)$$

Eq. (2) defines: $defalt_rate_{jt}$ (large exposure default rate), $NPL^{large}{}_{jt}$ (NPL's large exposure), and $D^{large}{}_{jt}$ (total exposures). Lagged effects are expected. Figure 2 shows the rate's trend. Figure (2) presents a bar chart of the large exposure default rate and its linear trend over the study period.

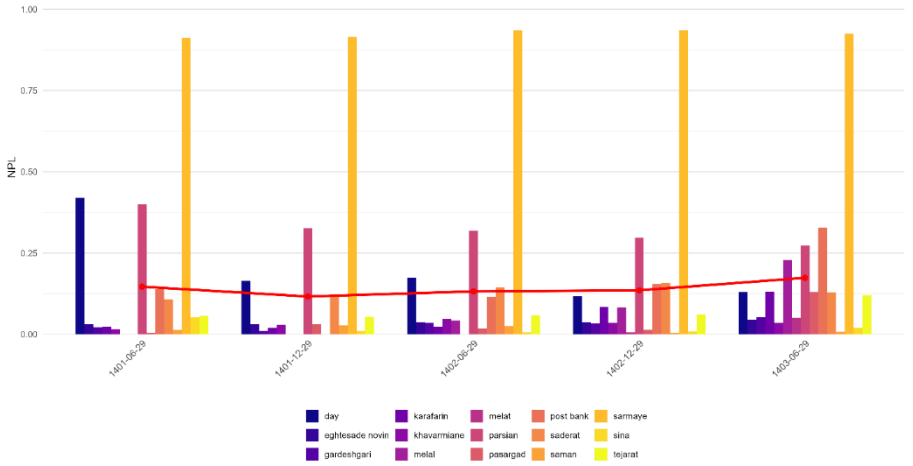

Figure 2. Temporal trend of the mean and bar chart of the default rate of large exposures for the sample banks
Source: Research Findings

Table 1 presents descriptive statistics revealing significant variation in default rates across banks, ranging from 1.14% (Melat Bank) to 92.44% (Sarmayeh Bank), this indicates substantial heterogeneity in credit risk management practices.

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Table 1
Statistical characteristics of the default rate of large exposures during the study period

Bank	mean	median	mod	min	max	variance	Standard Deviation
Eghtesad Novin	0.0364	0.037	0.037	0.031	0.045	0	0.0055
Parsian	0.3234	0.319	0.273	0.273	0.401	0.0023	0.0482
Pasargad	0.0392	0.017	0.004	0.004	0.13	0.0027	0.0517
Post Bank	0.1472	0.139	0	0	0.328	0.0139	0.1178
Tejarat	0.07	0.059	0.054	0.054	0.12	8.00E-04	0.0281
Khavarmiane	0.0326	0.035	0.016	0.016	0.047	1.00E-04	0.0113
Dey	0.2014	0.165	0.118	0.118	0.42	0.0155	0.1244
Saman	0.0154	0.013	0.004	0.004	0.027	1.00E-04	0.0102
Sarmaye	0.9244	0.925	0.935	0.912	0.935	1.00E-04	0.0108
Sina	0.0196	0.011	0.006	0.006	0.052	4.00E-04	0.0188
Saderat	0.1328	0.129	0.108	0.108	0.158	4.00E-04	0.0193
Karafarin	0.0564	0.024	0.02	0.02	0.131	0.0025	0.0495
Gardeshgari	0.0312	0.034	0.011	0.011	0.053	2.00E-04	0.0158
Melat	0.0114	0	0	0	0.051	5.00E-04	0.0223
Melal	0.0708	0.042	0	0	0.229	0.009	0.0949

Source: Research Findings

4.2.2 Independent Variables: Concentration Measures

A) Herfindahl-Hirschman Index (HHI)

The measurement methods of single-name credit concentration can be classified into two general categories: non-model (heuristic) methods and model-based methods. The first method enters the discussion using concentration measurement indices like the Herfindahl-Hirschman Index (Kwoka, 1977) and Gini coefficient (Gini, 1921). The second approach is the granularity adjustment method suggested by Gordy (2003, 2004) (Uberti & Figini, 2010). In the present research, concentration measurement is performed based on the Herfindahl-Hirschman Index (HHI).

In the literature, the Herfindahl-Hirschman Index (HHI), developed by Herfindahl (1959) and Hirschman (1964), has been widely used to measure sectoral concentration levels. This index is calculated by summing the squares of relative credit risk shares.

Considering the availability of information on single beneficiaries of large exposure borrowers, the Herfindahl-Hirschman concentration index for measuring the distribution of large exposures can be calculated as shown in Equation (3).

$$HHI_{jt} = \sum_i \left(\frac{d_{ijt}}{D^{large}_{jt}}\right)^2 \quad (3)$$

In Equation (3), we have:

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HHI_{jt}: Herfindahl-Hirschman Index (HHI) of large exposure concentration for bank *j* at time *t*

d_{ijt}: Outstanding large exposure to single beneficiary *i* of bank *j* at time *t*

$D^{large}{}_{jt}$: Total outstanding large exposures of bank *j* at time *t*

The aforementioned concentration index is derived from the sum of the squares of the ratio of individual large beneficiaries' outstanding loans to the bank's total outstanding large exposures at a given time. The values of this index range between 0 and 1, such that values closer to 1 indicate greater concentration of facilities among specific individuals and lack of diversification. Figure (3) presents a bar chart of banks' concentration indices over time.

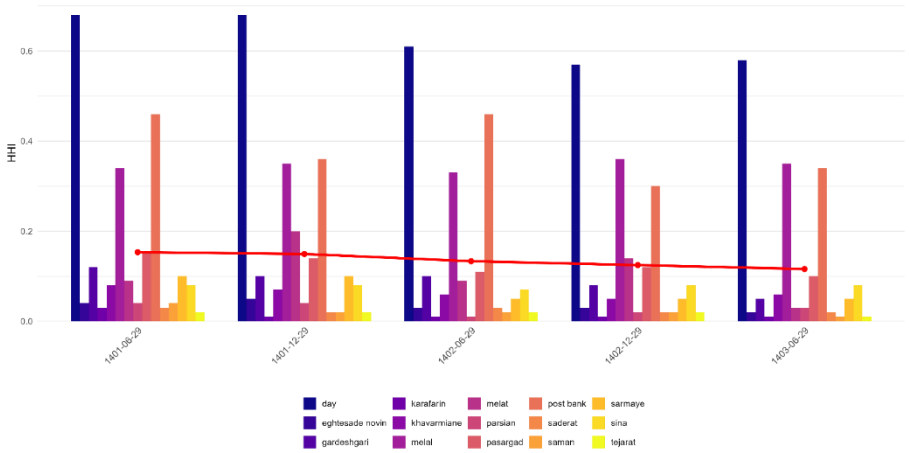

Figure 3: Temporal trend of the mean and bar chart of the Herfindahl-Hirschman Index (HHI)
Source: Research Findings

It should be noted that during the study period, the average concentration index in large credit distribution for the sample banks was 14%.

B) Large Exposure Concentration Ratio (CON)

Another criterion for measuring concentration in loan distribution is the allocation of loans between large and non-large exposures. To measure the concentration ratio of credits in the large exposure sector, the ratio of large exposures to total loans can be used, as specified in Equation (4).

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$$CON_{jt} = \frac{D^{large}{}_{jt}}{D_{jt}} \quad (4)$$

Equation (4) Components:

CON_{jt}: The concentration ratio of bank *j*'s large-scale credit facilities at time *t*.

$D^{large}{}_{jt}$: The total outstanding balance of large-scale credit facilities extended by bank *j* at time *t*.

D_{jt}: The total outstanding balance of all credit facilities (both large- and non-large-scale) issued by bank *j* at time *t*.

A higher value of CON_{jt} indicates greater concentration of bank *j*'s portfolio in large-scale credit facilities. Figure (4) presents the linear trend of the average concentration ratio over time.

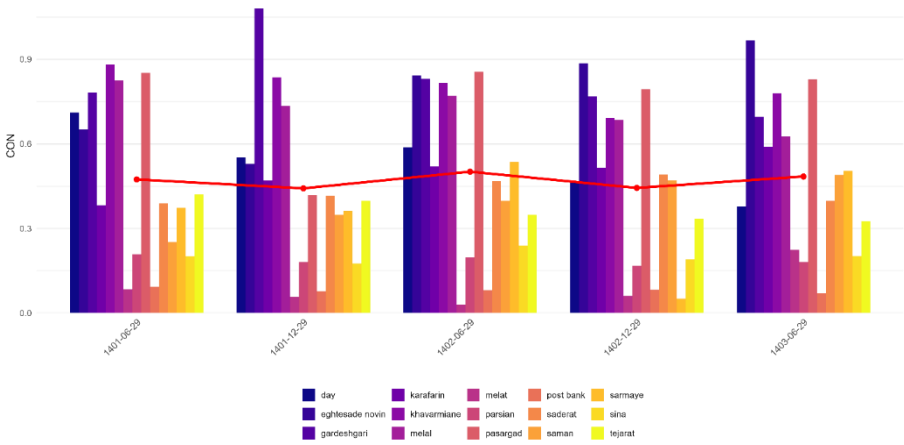

Figure 4. Temporal trend of the mean and bar chart of the large exposure ratio
Source: Research Findings

It should be noted that during the study period the average ratio of large loans to total credits stood at 47%.

4.2.3 Control Variables

A) Loan-to-Deposit Ratio (LDR)

The Loan-to-Deposit Ratio (LDR) is a commonly used statistical performance indicator employed to assess bank liquidity, reflecting the institution's resource utilization policy. This ratio demonstrates the

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relationship between a bank's total loan portfolio and funds received from third parties (deposits). Third-party funds include current/sight deposits, time deposits, and certificates of deposit, excluding interbank borrowings. The total loan amount comprises all payable loans excluding those extended to other banking institutions (Lew & Lau, 2022).

A high LDR indicates greater liquidity risk for the bank, while a low LDR suggests inefficiency in loan allocation. This ratio is derived by comparing the bank's total loans to its total deposits, representing the percentage of the loan portfolio funded by third-party deposits. Any increase in this ratio implies that the bank's loan volume is growing faster than its deposit base, reflecting greater resource allocation to lending activities. This situation may signal weak bank liquidity (ibid.).

The Loan-to-Deposit Ratio (LDR) reflects banks' liquidity management practices. According to Central Bank statistics, banks are permitted to allocate 75-80% of their deposit base (after statutory reserve deductions) as credit facilities. This ratio indicates the percentage of public deposits that banks have converted into income-generating assets, thereby enhancing their profit-sharing revenue (Nasiri Aghdam et al., 2019). Figure 5 presents both the cross-sectional distribution (bar chart) of this ratio across sample banks and its temporal trend (line graph) during the study period.

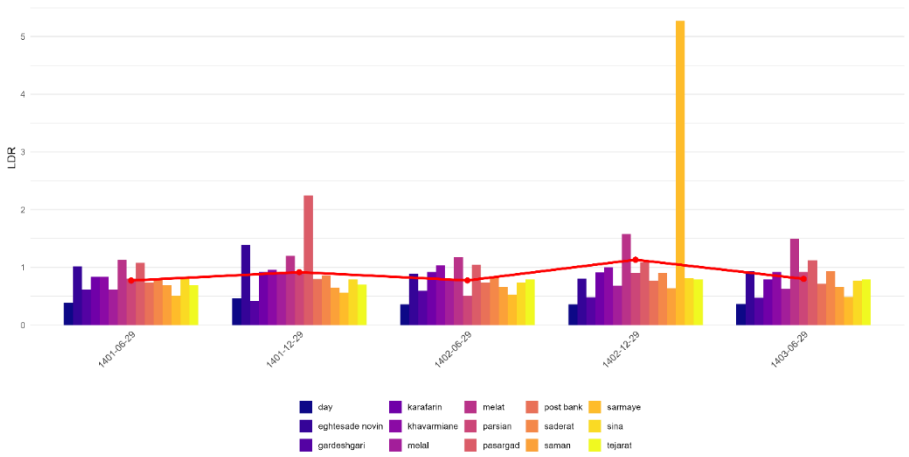

Figure 5. Temporal Trend (Line Graph) and Cross-Sectional Distribution (Bar Chart) of Loan-to-Deposit Ratios in Sample Banks
Source: Research Findings

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Furthermore, the average ratio throughout the study period was 88%. Theoretically, higher values of this ratio should enhance the bank's risk management capacity and consequently exert a positive effect on reducing loan default rates.

B) Capital Adequacy Ratio (CAR)

The Capital Adequacy Ratio (CAR) is calculated by dividing a bank's core capital by its total risk-weighted assets (Central Bank of I.R. Iran Banking Regulation on Capital Adequacy, 2011). Capital adequacy serves as a crucial indicator for protecting banks' debt repayment capacity and profitability, representing one of the most fundamental metrics in financial markets. This importance stems from information asymmetries between banks and borrowers, which may lead to loan defaults. Loan defaults result in bank losses, thereby obliging banks to maintain sufficient capital and operate efficiently to prevent bankruptcy (Khaksar Astaneh & Gohar Rostami, 2023). Consequently, it is expected that an increase in the capital adequacy ratio would reduce loan default rates.

According to the Capital Adequacy Regulations issued by the Supreme Council of Money and Credit, the minimum capital adequacy ratio for all banks and credit institutions is set at 8%. However, the average capital adequacy ratio for the sample banks during the study period was -22% (indicating severe capital insufficiency among sample banks). Figure 6 presents a bar chart showing the capital adequacy ratios of individual banks along with a line graph representing their average.

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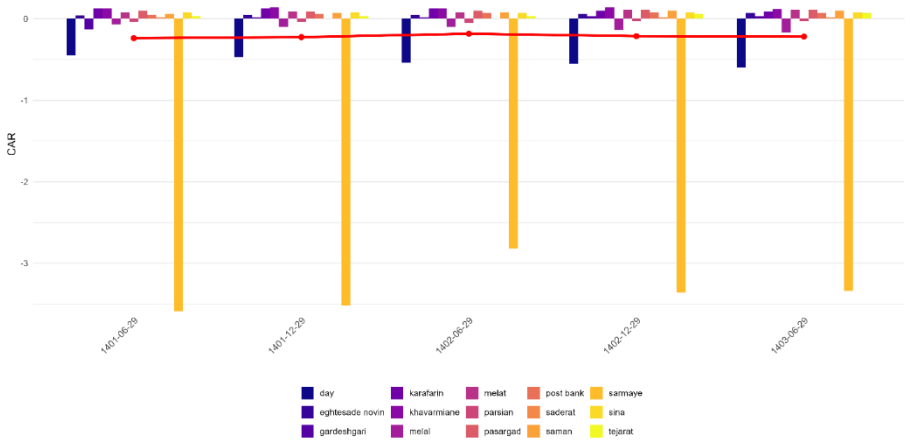

Figure 6. Time Trend of the Average Capital Adequacy Ratio and Corresponding Bar Chart for Sample Banks
Source: Research Findings

4.3 Empirical Strategy and Identification

The empirical strategy employs a two-step System GMM estimator with Windmeijer (2005) corrected standard errors to address the dynamic panel bias. Lagged levels of the endogenous variables are used as instruments for the differenced equation, and lagged differences serve as instruments for the level equation.

The exclusion of macroeconomic variables represents a deliberate choice, as they affect all banks symmetrically and are absorbed by time fixed effects. This approach follows recent empirical banking literature that focuses on bank-specific determinants of credit risk (Berger et al., 2009).

Diagnostic tests will include: (1) the Arellano-Bond test for serial correlation; (2) the Hansen test for instrument validity; and (3) difference-in-Hansen tests for exclusion restriction validity. The empirical results will be presented following these validation procedures.

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5 Model Tests and Empirical Outputs: Comprehensive Analysis and Extended Interpretation

5.1 Preliminary Data Analysis and Diagnostic Testing

Table 2 presents the Pearson correlation coefficients among the model variables, offering initial insights into their bivariate relationships. The results reveal several noteworthy patterns:

Table 2
Linear Correlation Coefficients Between Variables During the Study Period

Variable	NPL	HHI	CON	LDR	CAR
NPL	1	0.023945	-0.19254	0.195967	-0.92094
HHI	0.023945	1	0.000931	-0.20975	-0.04471
CON	-0.19254	0.000931	1	-0.22062	0.091526
LDR	0.195967	-0.20975	-0.22062	1	-0.22089
CAR	-0.92094	-0.04471	0.091526	-0.22089	1

Source: Research Findings

- NPL and CAR exhibit a strong negative correlation (-0.92094), suggesting that better-capitalized banks experience lower default rates, consistent with the bank monitoring hypothesis (Mehran & Thakor, 2011; Berger et al., 2009).
- NPL and LDR show a moderate positive correlation (0.195967), indicating potential liquidity-risk linkages, though this relationship requires multivariate analysis for proper interpretation.
- The weak correlation between HHI and NPL (0.023945) suggests that the relationship between name concentration and credit risk is not linear and may be influenced by other mediating factors.
- The low correlation among independent variables (all below 0.25) suggests that multicollinearity is not a significant concern in the model specification.

Table 3 presents the results of preliminary panel specification tests, which guided the selection of the appropriate estimation methodology:

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Table 3
Preliminary Panel Model Specification Tests

Test	F_statistic	p_value	df
Between vs Pooled	3.407008	0.027009	45,9
Within vs Pooled	1.753228	0.082548	14,40
Hausman (FE vs RE)	12.58477	0.027597	

Source: Research Findings

- The significant cross-sectional heterogeneity (F = 3.407, p = 0.027) indicates substantial heterogeneity across banks, justifying the use of panel data methods over pooled estimation.
- The Hausman test (χ^2 = 12.585, p = 0.028) rejects the null hypothesis, indicating that fixed effects are preferred over random effects due to correlation between unobserved bank characteristics and the explanatory variables.
- The negligible time effects (Wald p = 0.94) suggest that common temporal shocks affecting all banks simultaneously are relatively limited during the study period, though time fixed effects are retained for completeness.

5.2 System GMM Estimation Results and Interpretation

Table 4 presents the results of the two-way dynamic panel model estimated using the System Generalized Method of Moments (GMM) approach. The model demonstrates several economically significant relationships:

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Table 4
Estimation Results of the Two-Way Dynamic Panel Model

	Dependent variable:
	Non-Performing Large Facilities Ratio (NPL)
Lagged NPL (t-1)	0.387**
	(0.172)
Herfindahl-Hirschman Index (HHI)	-0.186***
	(0.061)
Lagged Large Facilities Ratio (CON(t-1))	-0.054
	(0.053)
Lagged Loans-to-Deposits Ratio (LDR(t-1))	-0.023**
	(0.011)
Lagged Capital Adequacy Ratio (CAR(t-1))	-0.156***
	(0.046)
Observations	15
Note:	*p<0.1; **p<0.05; ***p<0.01
	Model estimated with two-way (time and individual) effects.
	Sargan test fails to reject the null of valid instruments (p-value = 0.091).
	Second-order autocorrelation test rejects presence of autocorrelation (p-value = 0.389).
	All Wald tests confirm the overall significance of the model.

Source: Research Findings

5.2.1 Dynamic Persistence of Non-Performing Loans

The lagged dependent variable (default ratet-1) shows a statistically significant positive coefficient ($\beta = 0.39$, $p < 0.01$), indicating strong persistence in NPLs. This finding aligns with the "credit quality stickiness"** hypothesis, which suggests that deterioration in loan portfolio quality tends to persist over time due to both economic and institutional factors (Louzis et al., 2012; Ghosh, 2015). This persistence may reflect several mechanisms: (1) the time-intensive nature of workout processes for troubled loans; (2) regulatory forbearance practices; and (3) the procyclical nature of credit risk recognition (Bouvatier et al., 2014).

5.2.2 Name Concentration and Credit Risk

The Herfindahl-Hirschman Index (HHI) demonstrates a statistically significant negative coefficient ($p < 0.05$), indicating that increased name concentration is associated with lower default rates in large exposures. This finding supports the relationship banking theory (Boot, 2000; Berger et al., 2009) which posits that concentrated lending relationships enable banks to develop superior monitoring capabilities, gather proprietary information, and establish stronger borrower discipline. In the Iranian context, where formal

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credit information systems are relatively underdeveloped, relationship-specific information gains through concentration may be particularly valuable.

5.2.3 Portfolio Composition and Credit Quality

The ratio of large loans to total loans (CON) shows a negative but statistically insignificant relationship with default rates. This suggests that the absolute share of large exposures in a bank's portfolio matters less for credit quality than how these exposures are distributed among borrowers (as captured by HHI). This finding aligns with Nokkala's (2022) contention that portfolio structure moderates the risk effects of large exposures

5.2.4 Liquidity Management and Credit Risk

The loan-to-deposit ratio (LDR) exhibits a statistically significant negative coefficient ($p < 0.05$), indicating that banks with higher lending activity relative to their deposit base experience lower default rates. This seemingly counterintuitive result may be explained by several mechanisms: (1) banks with superior credit assessment capabilities can simultaneously maintain higher LDRs and lower NPLs; (2) in a high-inflation environment such as Iran's, banks may be compelled to deploy deposits quickly to preserve value, creating selection pressure for better lending decisions; and (3) the relationship may be non-linear, with benefits reversing beyond certain thresholds (Kashyap et al., 2002).

5.2.5 Capital Adequacy and Risk Management

The capital adequacy ratio (CAR) shows a statistically significant negative coefficient ($p < 0.01$), strongly supporting the monitoring hypothesis of capital (Mehran & Thakor, 2011). Better-capitalized banks have more to lose from poor lending decisions and therefore invest more in screening and monitoring borrowers (Berger et al., 2009). This finding is particularly relevant given the severely negative average CAR (-22%) in the sample, suggesting that capital deficiency may be a fundamental driver of the high NPLs observed in the Iranian banking system.

5.3 Model Validation and Diagnostic Tests

Table 5 presents comprehensive diagnostic tests confirming the validity of the empirical approach:

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Table 5
Model Specification Diagnostic Tests

Test	Statistic	p_value
Sargan	15	0.091
AR(1)	-1.423	0.155
AR(2)	0.861	0.389
Wald test for coefficients	16281.43	<0.001
Wald test for time dummies		0.034

Source: Research Findings

- The Sargan test ($p = 0.091 > 0.10$) fails to reject the null hypothesis of instrument validity, indicating that the overidentifying restrictions are appropriate and the instruments are exogenous (Roodman, 2009).
- The Arellano-Bond tests for autocorrelation show: (1) no evidence of first-order autocorrelation in differences (AR(1), $p = 0.155$), which is expected and desirable; and (2) no second-order autocorrelation (AR(2), $p = 0.389$), supporting the assumption of no serial correlation in the error terms.
- The Wald tests indicate: (1) joint significance of all coefficients ($p < 0.001$); and (2) significance of time dummies ($p = 0.034$), justifying the inclusion of time fixed effects.

5.4 Robustness Considerations and Limitations

While the model performs well according to standard diagnostic tests, several limitations should be acknowledged:

- Short Time Dimension: With only five semi-annual observations, the estimates, though consistent, may have reduced efficiency (Roodman, 2009).
- Measurement Challenges: The self-reported nature of large exposure data and potential inconsistencies in borrower identification may introduce measurement error (BIS, 2017).
- Macroeconomic Omissions: While time fixed effects capture common shocks, bank-specific exposure to macroeconomic factors may vary and may introduce omitted variable bias (Ghosh, 2015).
- Generalizability: The extreme capital adequacy situation in the sample banks (-22% average CAR) may limit the direct transferability of findings to better-capitalized banking systems.

Despite these limitations, the model provides valuable insights into the relationships between concentration, bank-specific factors, and credit risk in

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the unique context of the Iranian banking system, contributing to both academic literature and policy discussions on managing concentration risk.

6 Discussion and Conclusions

This study provides robust empirical evidence that resolves the theoretical tension between diversification and specialization strategies in banking, particularly within the unique context of Iran's banking system characterized by significant financial distress and institutional constraints. Our findings provide strong empirical support for Winton's (1999) contingency theory, demonstrating that the relationship between concentration and credit risk is neither universally positive nor negative, but fundamentally depends on bank-specific factors and the type of concentration being examined.

The most significant finding that name concentration (HHI) is associated with lower default rates in large exposures challenges conventional diversification dogma and strongly supports the relationship banking theory (Boot, 2000; Berger et al., 2009). In an environment where formal credit information systems are relatively underdeveloped, concentrated lending relationships appear to generate valuable proprietary information that enhances monitoring effectiveness and borrower discipline. This mechanism is widely highlighted in the relationship lending literature in emerging markets and institutional settings.

While the System GMM estimator is designed to mitigate endogeneity concerns through the use of instrumental variables, and the results are consistent with a causal interpretation derived from Winton's (1999) theoretical model, the relatively short time dimension of the dataset necessitates a degree of caution in making definitive causal claims. The relationships identified are robust and economically significant, but further research with longer time series would help to more firmly establish causality.

The contrasting result for portfolio concentration (CON) showing no significant relationship with default rates suggests that what matters is not merely the volume of large exposures but their distribution among borrowers. This nuanced finding supports Nokkala's (2022) contention that portfolio structure moderates risk effects and underscores the importance of distinguishing between different dimensions of concentration.

The strong persistence of NPLs ($\beta = 0.39$) confirms the "credit quality stickiness" hypothesis and suggests that deteriorating loan quality creates negative path dependencies that are difficult to reverse (Louzis et al., 2012; Ghosh, 2015). This persistence likely reflects both institutional factors

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(regulatory forbearance, lengthy workout processes) and behavioral factors (evergreening of loans, reporting biases).

Our findings have several crucial policy implications for Iranian banking regulators and international policymakers facing similar contexts:

1) Precision Regulation: Blanket concentration limits may be counterproductive. Instead, regulators should adopt more nuanced approaches that distinguish between name concentration (which may be beneficial) and sectoral concentration (which may be riskier).
2) Capital Restoration: The severely negative capital adequacy ratios (-22% average) and their strong negative relationship with NPLs suggest that capital restoration should be the immediate priority. Better-capitalized banks not only absorb losses better but also appear to make better lending decisions.
3) Information Infrastructure: Investments in credit information systems could help replicate the relationship banking benefits more broadly across the system, potentially reducing the risk advantages of extreme concentration.
4) Supervisory Focus: Regulators should focus particularly on banks combining high concentration with weak capital positions, as these institutions likely pose the greatest systemic risk.

This study demonstrates that the effect of credit concentration on risk is fundamentally contingent shaped by the type of concentration, the institutional environment, and bank-specific factors. In Iran's banking system, name concentration in large exposures appears to serve as an adaptive response to institutional voids, generating information advantages that outweigh diversification benefits. However, this beneficial effect operates within the context of severe capital deficiency that remains the primary determinant of credit risk.

A primary limitation of this study is the unique context of the Iranian banking system, characterized by severely negative capital adequacy ratios, high inflation, and specific regulatory frameworks. Consequently, the generalizability (external validity) of these findings to other banking systems with different economic conditions, regulatory environments, and healthier capital bases may be limited. The results are most readily applicable to other emerging markets with similar institutional characteristics. Future research could test the contingency theory model developed here in other jurisdictions to explore its broader validity.

These findings contribute to the theoretical literature by validating Winton's contingency approach in a novel context and to policy discourse by

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demonstrating the need for precision regulation that acknowledges the complex, context-dependent nature of concentration risk. As banking systems worldwide grapple with the trade-offs between financial stability and credit availability, this research underscores that neither concentration nor diversification is inherently superior their effects depend crucially on how they interact with specific institutional and organizational contexts.

References

Acharya, V. V., Hasan, I., & Saunders, A. (2006). Should banks be diversified? Evidence from individual bank loan portfolios. *The Journal of Business, 79(3), 1355-1412.*

Adzobu, L. D., Agbloyor, E. K., & Aboagye, A. (2017). The effect of loan portfolio diversification on banks' risks and return: Evidence from an emerging market. *Managerial Finance, 43(11), 1274-1291*.

Alnabulsi, K., Kozarević, E., & Hakimi, A. (2023). Non-performing loans as a driver of banking distress A systematic literature review. *Commodities, 2(2), 111-130.*

Baltagi, B. H. (2013). *Dynamic panel data models*. Cambridge University Press.

Basel Committee on Banking Supervision. (2004). *Basel II: International convergence of capital measurement and capital standards: A revised framework*. Bank for International Settlements. https://www.bis.org/publ/bcbs107.htm

Basel Committee on Banking Supervision (2014). *Supervisory Framework for Measuring and Controlling Large Exposures*. Bank for International Settlements.

Basel Committee on Banking Supervision (2017). *Basel III: Finalising post-crisis reforms*. Bank for International Settlements.

Behr, A., Kamp, A., Memmel, C., & Pfingsten, A. (2007). *Diversification and the banks' risk-return-characteristics: Evidence from loan portfolios of German banks.* (Bundesbank Series 2 Discussion Paper No. 2007,05). Available at SSRN: https://ssrn.com/abstract=2793990

Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank competition and financial stability. *Journal of Financial Services Research, 35*(2), 99–118.

Boot, A. W. A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation, 9(1), 7-25*.

Bouvatier, V., Lepetit, L., & Strobel, F. (2014). Bank income smoothing, ownership concentration and the regulatory environment. *Journal of Banking & Finance, 41, 253-270.*

Brown, K., & Moles, P. (2014). *Credit risk management*. Edinburgh Business School.

Central Bank of Iran (CBI). (2004). *Regulation on Large Facilities and Commitments* (Session No. 1014, approved 25/11/1382 [16 February 2004]). Tehran: Money and Credit Council.

[Downloaded from jme.mbri.ac.ir on 2026-10-14]

[DOI: 10.66224/jme.20.4.501]

Chandramohan, K., Lunawat, C. D., & Lunawat, C. A. (2022). The impact of diversification on bank stability in India. *Cogent Business & Management, 9(1), 2094590*.

Chen, Y., Wei, X., & Zhang, L. (2013). A new measurement of sectoral concentration of credit portfolios. *Procedia Computer Science, 17, 1231-1240*.

Delova-Jolevska, E., & Andovski, I. (2013). Risk-based supervision of banks. *Horizons International Scientific Magazine,series A, Social Sciences and Humanities, 10*, 107-118.

Denis, D. J., Denis, D. K., & Sarin, A. (1997). Agency Problems, Equity Ownership and Corporate Diversification. *The Journal of Finance, Vol. 52, No.1, pp. 135-160*.

Diamond, D. W. (1984). Financial Intermediation and Delegated Monitoring. *The Review of Economic Studies, 51*(3), 393-414.

Ferreira, C. (2022). Determinants of non-performing loans A panel data approach. *International Advances in Economic Research, 28(3), 133-153*.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica, 79*(3), 733–772.

Galaasen, S., Jamilov, R., Juelsrud, R., & Rey, H. (2020). *Granular credit risk* (No. w27994). National Bureau of Economic Research.

Gini, C. (1921). Measurement of inequality of incomes. *The economic journal, 31(121), 124-125*.

Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability, 20, 93-104*.

Gordy, M. B. (2003). A risk-factor model foundation for ratings-based bank capital rules. *Journal of financial intermediation, 12(3), 199-232*.

Gordy, M. B. (2004). Granularity adjustment in portfolio credit risk measurement. In G. Szegö (Ed.), *Risk measures for the 21st century* .John Wiley & Sons.

Herfindahl, O. C. (1959). *Copper Costs and Prices*. Johns Hopkins Press.

Hibbeln, M. (2010). *Risk management in credit portfolios concentration risk and Basel II*. Springer Science & Business Media.

Hirschman, A.O. (1964). The paternity of an index. *American Economic Review. 54*, 761-762.

Huynh, J., & Dang, V. D. (2021). Loan portfolio diversification and bank returns Do business models and market power matter. *Cogent Economics & Finance, 9(1), 1891709*.

International Organization of Securities Commissions (IOSCO). (2009). *Guidelines to emerging market regulators regarding requirements for minimum entry and continuous risk-based supervision of market intermediaries* (Final Report). IOSCO Emerging Markets Committee.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American economic review, 76(2), 323-329*.

[Downloaded from jme.mbri.ac.ir on 2026-10-14]

[DOI: 10.66224/jme.20.4.501]

Kashyap, A. K., Rajan, R., & Stein, J. C. (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *The Journal of Finance, 57(1), 33-73*

Khaksar Astaneh, M., & Gohar Rostami, A. (2023). Examining the impact of capital adequacy on economic efficiency indicators of state-owned banks in Iran. *Quarterly Journal of Studies in Banking Management and Islamic Banking, 9(23), 1-24*. [In Persian]

Kwoka, J. E. (1977). Large firm dominance and price-cost margins in manufacturing industries. *Southern economic journal, 183-189*.

Kozak, S. (2015). Concentration of credit exposure as a significant source of risk in banking activities: the idea and methods of estimation. *Financial Internet Quarterly, 11(3), 103-115.*

Le, T. T., & Diep, T. T. (2020). The effect of lending structure concentration on credit risk: The evidence of Vietnamese Commercial Banks. *Journal of Asian Finance, Economics and Business, 7(7), 59–72 59*.

Lew, B. Y., & Lau, W. T. (2022). Credit risk and commercial bank performance: Evidence from ASEAN. *International Journal of Academic Reserach in Economics and Management Sciences, 11(3).*

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of banking & finance, 36(4), 1012-1027*.

Markowitz, H. M. (1959). *Portfolio Selection Efficient Diversification of Investments*. Yale University Press.

Mehran, H., & Thakor, A. (2011). Bank capital and value in the cross-section. *The Review of Financial Studies, 24(4), 1019-1067*.

Nasiri Aghdam, A., Mohajeri, P., & Afruzkelardehi, E., (2019). The Effect of Ownership on the Performance of the Banking System in Iran. *Quarterly Journal of Economic Research and Policies, 27*(89), 269-298. [In Persian]

Nokkala, J. (2022). Are large credit exposures a source of concentration risk? *Bank I Kredyt, 53(4), 375-398*.

Nokkala, J. (2025). *Essays on the Empirical Measurement of Banks' Credit Portfolio Risks* (Doctoral dissertation, Itä-Suomen yliopisto).

Raei, R., Farhangzadeh, B., Safizadeh, M., & Raei, F. (2016). Study of the relationship between credit diversification strategy and banks' credit risk and return: evidence from Tehran stock exchange (TSE). *Procedia Economics and Finance, 36, 62-69*.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal, 9(1), 86-136*

Şahin, A., & Acar, E. (2024). Sectoral Concentration in Loans and Credit Risk: An Examination by Company Accounts in Turkey. *Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty, 11(4), 1392-1410*.

[Downloaded from jme.mbri.ac.ir on 2026-10-14]

[DOI: 10.66224/jme.20.4.501]

Tabak, B. M., Fazio, D. M., & Cajueiro, D. O. (2011). The effects of loan portfolio concentration on Brazilian banks' return and risk. *Journal of Banking & Finance, 35(11), 3065-3076.*

Uberti, P., & Figini, S. (2010). How to measure single-name credit risk concentrations. *European Journal of Operational Research, 202(1), 232-238*.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25–51.

Winton, A. (1999, September 27). *Don't put all your eggs in one basket? Diversification and specialization in lending*. SSRN. https://doi.org/10.2139/ssrn.173615

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

[Downloaded from jme.mbri.ac.ir on 2026-10-14]

[DOI: 10.66224/jme.20.4.501]