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Supply Chain Concentration and Corporate Default Risk: Evidence from China

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Abstract: Supply chain concentration constitutes a pivotal governance structure shaping corporate operational resilience. Using data on Chinese A-share listed firms from 2001 to 2022, this study estimates expected default probability via the KMV model and employs a random-effects Tobit model to correct for left-censoring in the dependent variable. Panel estimation results reveal that elevated supply chain concentration significantly reduces corporate default probability, with this effect operating through both customer concentration and supplier concentration dimensions. To address endogeneity, we construct an instrumental variable using the number of Ming Dynasty post stations and apply the control function approach to correct for bias. The corrected estimates confirm the risk mitigation effect of supply chain concentration.

Keywords: Supply Chain Concentration; Customer Concentration; Default Risk; Supplier Concentration

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1. Introduction

Against the backdrop of global value chain restructuring and the elevation of industrial chain security to national strategic priority, supply chain stability and resilience have become critical variables influencing macroeconomic performance. In recent years, from global supply chain disruptions triggered by the COVID-19 pandemic (Li et al., 2023), to raw material shortages caused by geopolitical conflicts, and bottlenecks in critical components, frequent supply chain risk events have not only impacted micro-level corporate operations but also evolved into threats to systemic financial stability through credit linkages and risk contagion mechanisms among enterprises (Ağca et al., 2022). Notably, government support policies play an important role in alleviating corporate financing constraints and enhancing survival capabilities, yet such supportive effects may exhibit nonlinear boundaries (Han et al., 2024). As node enterprises within supply chain networks, corporate defaults reflect not merely individual financial distress but may trigger chain reactions through debt linkages, amplifying risks across entire industries and even the financial system (Xie et al., 2023). Therefore, identifying the intrinsic relationship between supply chain structural characteristics and corporate default risk holds significant practical importance for preventing and resolving major financial risks and safeguarding industrial and supply chain security.

However, existing literature has primarily focused on internal governance dimensions such as equity structure and board characteristics, while research on how informal institutional networks (e.g., chambers of commerce and industry associations as social capital vehicles) influence cross-border resource allocation has grown increasingly prevalent (Wang et al., 2025). Nevertheless, examination of supply chains as external governance mechanisms remains insufficient. Supply chain relationships serve as carriers of implicit contracts between enterprises and possess governance functions; deep collaboration can reduce information asymmetry and enhance operational stability, yet excessive dependence may amplify operational uncertainty and risk contagion effects. Under this divergence, how does supply chain structure influence corporate default risk? Answering this question not only helps clarify the microeconomic consequences of supply chain management but also provides empirical evidence and policy references for improving corporate governance mechanisms and strengthening risk prevention systems.

Existing research exhibits three limitations regarding core conclusions, methodology, and identification strategies. First, in terms of core conclusions, Fang et al. (2023) found that supply chain concentration is significantly positively correlated with default risk, meaning higher concentration leads to higher expected default probability, with mechanisms operating through crowding-out effects on innovation investment and performance. Other studies have focused on the impact of customer concentration on cash flow risk (Mihov & Naranjo, 2017), stock price crash risk (Ma et al., 2020), corporate risk-taking (Cao et al., 2021), and loan contract terms (Campello & Gao, 2017), yet direct examination of the relationship between supply chain concentration and default risk remains insufficient. Although Shen and Chen (2023) studied default risk among supply chain enterprises, they focused on the U-shaped effect of short-term debt for long-term use, treating customer effects merely as moderating variables without directly testing the net effect of supply chain concentration itself on default risk. Second, methodologically, existing literature generally employs OLS or standard linear panel regression (e.g., Fang et al., 2023), ignoring the substantial left-censoring of default probability at zero, which leads to inconsistent estimators. Third, regarding identification strategy, supply chain concentration is likely endogenous; firms with lower default risk may self-select into more concentrated supply chain networks, yet existing research has failed to effectively address this endogeneity bias or introduce appropriate instrumental variables for causal identification.

Addressing these gaps, the marginal contributions of this study are threefold. First, regarding core conclusions, this study finds that increased supply chain concentration significantly reduces corporate default probability, supporting the risk mitigation effect of concentration and providing new empirical evidence for the debate on supply chain structure. Second, methodologically, this study systematically applies the RE-Tobit model to this field for the first time, effectively correcting estimation bias caused by left-censoring of default probability; simultaneously, it adopts the control function approach proposed by Blundell and Powell (2004), constructing an instrumental variable using the historical geographic variable of Ming Dynasty post station numbers, obtaining more reliable causal effects through two-stage estimation. Third, regarding mechanism analysis, this study decomposes the effect into customer concentration and supplier concentration, revealing complementary transmission channels through downstream demand stability and upstream supply security in mitigating default risk, filling the gap in micro-level mechanism evidence.

2. Theories and Hypothesis

Social capital theory and resource dependence theory posit that firms are embedded within networks composed of upstream suppliers and downstream customers (Portes, 1998). Within these networks, trust and repeated interactions serve as implicit contracts, restraining opportunistic behavior and reducing monitoring costs. For firms operating in volatile environments, concentrated supply chains can function as stable resource channels: core suppliers ensure production continuity through prioritized capacity allocation, while key customers provide predictable cash flows, thereby smoothing revenue volatility. From this perspective, supply chain concentration can reduce transaction costs, compress information asymmetry, and ultimately increase default distance while lowering default probability (PD).

However, resource dependence theory also cautions that excessive reliance on a limited number of partners creates lock-in effects. Once dominant suppliers or customers encounter liquidity shocks, distress will transmit along the supply chain, amplifying the focal firm's default risk (Guo et al., 2024). Furthermore, network homophily may trap firms in information echo chambers, distorting resource allocation and amplifying vulnerability (McPherson et al., 2001). Through this lens, higher concentration narrows default distance and increases default probability.

Given the theoretical ambiguity regarding the net effect of supply chain concentration on default risk, this study proposes the following competing hypotheses, H1a: Ceteris paribus, increased supply chain concentration enlarges default distance, thereby reducing corporate default risk.

H1b: Ceteris paribus, increased supply chain concentration narrows default distance, thereby exacerbating corporate default risk.

As a composite indicator, supply chain concentration masks differentiated transmission mechanisms between upstream and downstream. Drawing on existing literature regarding decomposition of supply chain network structure (Patatoukas, 2012; Wu and Yao, 2023), this study disaggregates SCCD into customer concentration (CC) and supplier concentration (SC) to separately test their risk mitigation pathways.Downstream channel: Demand stability mechanism. Customer concentration reflects the concentration degree of a firm's revenue streams. When firms depend on a limited number of core customers, although they face demand interruption risks, deep collaborative relationships can reduce sales volatility, shorten accounts receivable cycles, and provide stable cash flow expectations (Campello & Gao, 2017). This demand stability directly improves firms' short-term solvency and interest coverage ratios, thereby expanding default distance. Accordingly, this study proposes,

H2a: Increased customer concentration reduces corporate default probability by enhancing demand stability.

Upstream channel: Supply security mechanism. Supplier concentration reflects the concentration degree of a firm's input sources. Establishing long-term relationships with core suppliers ensures prioritized raw material supply, reduces search costs and bargaining costs, and provides capacity guarantees during supply chain disruptions. This supply security reduces production stagnation risks and inventory accumulation costs, stabilizing firms' cost structures and profit margins, thereby reducing default probability. Accordingly, this study proposes,

H2b: Increased supplier concentration reduces corporate default probability by enhancing supply security.

These two channels are not mutually exclusive but complementary: downstream demand stability safeguards cash inflows, while upstream supply security controls cost expenditures, both jointly affecting corporate default distance. If H1a holds, both H2a and H2b should be simultaneously validated; if H1b holds, at least one channel should be insignificant or exhibit opposite direction.

Supply chain concentration is likely endogenous: firms with lower default risk may self-select into more concentrated supply chain networks, or omitted governance quality factors may simultaneously influence both. To obtain causal effects, instrumental variables satisfying both relevance and exogeneity conditions must be identified.

This study employs the number of Ming Dynasty post stations in prefecture-level cities where firms are located as the instrumental variable, with the following logical foundations,

Relevance condition. Ming Dynasty post stations served as core nodes for information transmission and material allocation during the imperial period, with site selection following principles of geographic continuity and accessibility to all directions, prioritizing transportation hubs with active commerce and trade. These historical transportation nodes shaped the logistics network foundations and commercial agglomeration traditions of contemporary cities, making firms in these regions more likely to form close supply chain cooperative relationships. Therefore, the number of Ming Dynasty post stations is positively correlated with contemporary supply chain concentration.

Exogeneity condition. The layout of Ming Dynasty post stations was determined by military defense and administrative transmission requirements, bearing no direct relationship with contemporary corporate default risk. Post station numbers remain constant over time, absorbing permanent unobservable city characteristics such as geographic endowments and historical hub status, which may influence contemporary economic structures but do not directly affect individual corporate default behavior. Moreover, as a historical variable, post stations are uncorrelated with endogenous disturbances in contemporary supply chain policy, satisfying the exclusion restriction.

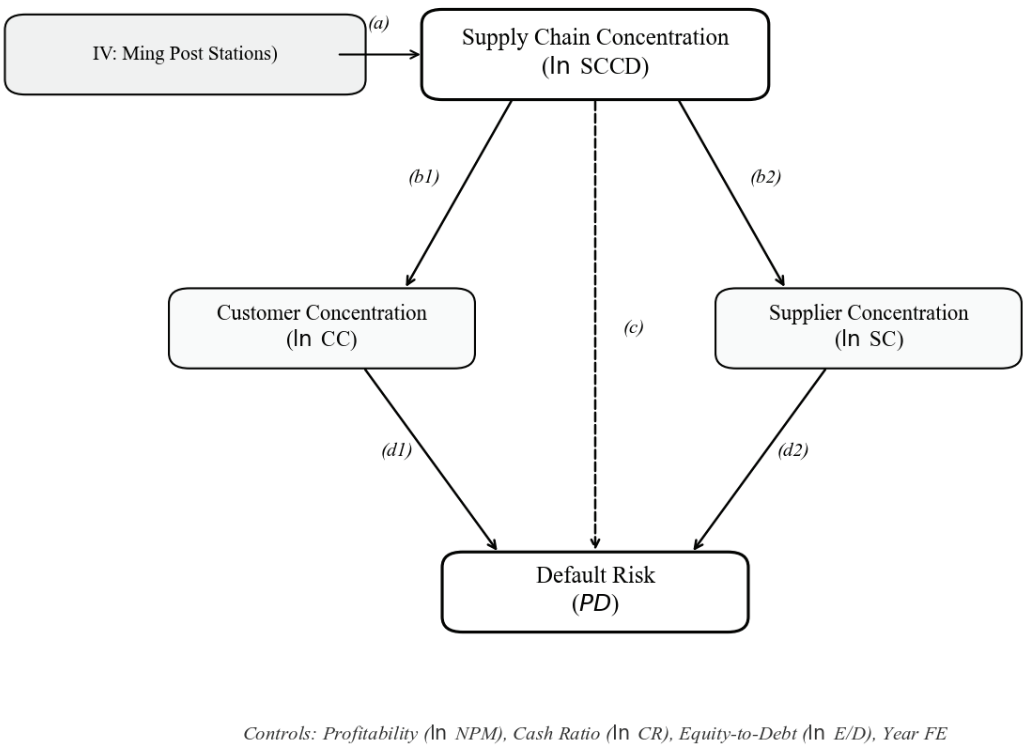
Based on the above analysis, this study proposes,

H3: The number of Ming Dynasty post stations is significantly positively correlated with supply chain concentration, satisfying the relevance requirement for instrumental variables; and this instrumental variable is exogenous to corporate default risk, satisfying the exclusion restriction.

Figure 1 illustrates the mechanism transmission pathways through which supply chain concentration affects default risk.

This figure presents the conceptual framework and empirical strategy of this study. Pathway (a) represents the first-stage regression, using the number of Ming Dynasty post stations as the instrumental variable (IV) to identify the exogenous variation in supply chain concentration (ln SCCD). Pathway (c) depicts the direct effect of supply chain concentration on corporate default probability (PD) (H1). Pathways (b1) and (b2) decompose supply chain concentration into customer concentration (lnCC) and supplier concentration (lnSC). Pathways (d1) and (d2) represent two mechanism transmission channels: customer concentration affects default risk through demand stability (H2a), while supplier concentration operates through supply security (H2b). All regressions control for net profit margin (lnNPM), cash ratio (lnCR), equity-to-debt ratio (lnE/D), and year fixed effects.

Figure 1 Mechanism Transmission of Supply Chain Concentration on Default Risk



3. Empirical Strategy

3.1 Sample Selection and Data Sources

This study examines Chinese A-share listed companies from 2001 to 2022, constructing an unbalanced panel dataset. Sample selection follows these criteria: (1) financial sector listed companies are excluded to avoid interference from their distinctive capital structures; (2) ST and ST firms are excluded; (3) observations with missing key variables are excluded; (4) to mitigate extreme value effects, continuous variables are trimmed at the 1st and 99th percentiles, meaning observations outside this range are directly deleted. After these screenings, the final sample comprises 31,561 firm-year observations. Data sources include the CSMAR and Wind databases.

3.2 Variable Declaration

The dependent variable in this study is corporate default risk. Following Bharath and Shumway (2008) and Deren X and Jinsong L (2022), we select PD_{it} as the indicator for measuring corporate default risk. The specific calculation formulas are as follows.

First, corporate default probability PD_{it} is obtained by transforming default distance DD_{it} through the standard normal cumulative density function:

$$PD_{it}=N(-DD_{it}) \tag{1}$$

In equation (1), N(\cdot) denotes the standard normal cumulative density function.

Second, default distance DD_{it} measures the degree to which corporate asset market value deviates from the default point, calculated as:

$$DD_{it}=\frac{V_{it}-VD_{it}}{V_{it}\cdot\sigma_{V,it}} \tag{2}$$

In equation (2), V_{it} represents corporate asset market value, obtained through simultaneous iterative solution of equations (4) and (5);VD_{it} represents the default point (F_{it}) Calculated as the aggregate of current liabilities and 0.5 times the non - current liabilities at the end of the year.; and $\sigma_{V,it}$ epresents corporate asset value volatility.

Furthermore, corporate asset value volatility $\sigma_{V,it}$ is calculated through weighted combination of equity value volatility $\sigma_{E,it}$ and debt volatility $\sigma_{D,it}$.

$$\sigma_{V,it}=\frac{VE_{it}}{VE_{it}+VD_{it}}\cdot\ \sigma_{E,it}+\frac{VD_{it}}{VE_{it}+VD_{it}}\cdot\ \sigma_{D,it}=\frac{VE_{it}}{VE_{it}+VD_{it}}\cdot\ \sigma_{Eit}+\frac{VD_{it}}{VE_{it}+VD_{it}}\cdot\ \left(0.05+0.25\cdot\ \sigma_{E,it}\right) \tag{3}$$

In equation (3), VE_{it} represents the equity market capitalization, which is defined as the product of the total number of outstanding shares and the stock price at year end ; $\sigma_{E,it}$ represents equity value volatility, measured by the monthly stock return standard deviation over the previous year; $\sigma_{D,it}$ represents debt volatility, approximated based on equity volatility as $\sigma_{D,it}=0.05+0.25\left(0.05+0.25\cdot\ \sigma_{E,it}\right)$.

Finally, solving for V_{it} and $\sigma_{V,it}$ requires simultaneous solution of the following two equations. Equation (4) is the Black-Scholes option pricing equation:

$$VE_{it}=V_{it}\cdot N\left(\frac{\ln(\frac{V_{it}}{F_{it}})+(r_{it}+0.5\sigma_{V,it}^{2})\cdot T}{\sigma_{V,it}\cdot\sqrt{T}}\right)-F_{it}\cdot e^{-r_{it}\cdot T}\cdot N\left(\frac{\ln(\frac{V_{it}}{F_{it}})+(r_{it}+0.5\sigma_{V,it}^{2})\cdot T}{\sigma_{V,it}\cdot\sqrt{T}}-\sigma_{V,it}\cdot\sqrt{T}\right) \tag{4}$$

In equation (4), VE_{it} represents equity market value; r_{it} represents the risk-free rate, calculated using one-year time deposit interest rates weighted by time; and T denotes debt maturity, set at 1 year.

Equation (5) is the volatility relation.

$$\sigma_{E,it}=N\left(\frac{\ln(\frac{V_{it}}{F_{it}})+(r_{it}+0.5\sigma_{V,it}^{2})\cdot T}{\sigma_{V,it}\cdot\sqrt{T}}\right)\cdot\frac{V_{it}}{E_{it}}\cdot\sigma_{V,it} \tag{5}$$

Through simultaneous solution of equations (4) and (5) using iterative methods, corporate asset market value V_{it} and asset value volatility $\sigma_{V,it}$ are obtained. Substituting these into equation (2) yields default distance DD_{it} and subsequently default probability PD_{it} through equation (1). A larger DD_{it} value indicates higher safety margin between corporate asset value and the default point, meaning lower default probability PD_{it} and lower default risk.

The explanatory variable is supply chain concentration (SCCD). Following Qiang W and Yu-xiu Y (2023), this study measures enterprise supply chain concentration using the mean of the sum of supplier concentration (SC) and customer concentration (CC), with specific calculation formulas as follows.

$$SC=\frac{\sum_{i=1}^{n} S\,C}{n} \tag{5}$$

$$CC=\frac{\sum_{i=1}^{n} CC}{n} \tag{6}$$

$$SCCD=\frac{SC+CC}{2} \tag{7}$$

In equations (5) and (6), supplier concentration and customer concentration are expressed as averaged sums. Supplier concentration is measured by the proportion of total annual procurement from the top five suppliers relative to total annual procurement; customer concentration is measured by the proportion of total annual sales to the top five customers relative to total annual sales; and equation (7) calculates listed company supply chain concentration as the mean of customer concentration and supplier concentration.

This study introduces net profit margin (lnNPM), cash ratio (lnCR), and equity to debt ratio (lnE/D) as control variables. Additionally, year dummy variables are included to control for macro-level unobservable shocks. See Tables 1 and 2 for details.

Table 1 Descriptive statistics of variables

variable	Obs	Mean	Std. dev.	Min	Max
PD	31,561	0.202	0.282	0	1
lnSCCD	31,561	3.385	0.516	1.723	4.456
lnCC	31,561	3.202	0.795	0.231	4.584
lnSC	31,561	3.390	0.579	1.635	4.556
lnNPM	31,561	0.190	0.168	-4.605	0.504
lnCR	31,561	-0.935	1.163	-4.692	2.297
LnE/D	31,561	0.416	0.968	-2.847	2.999
IV	31,561	3.582	3.838	0	19
Year	31,561	2016.279	5.297	2001	2022

Table 2 Description of the main variables

variable	Variable Description
PD	Default Probability Ratio
lnSCCD	The mean of the sum of the procurement proportions from the top five suppliers and the sales proportions from the top five customers (truncated logarithm
lnCC	The proportion of sales to the top five customers in total annual sales (truncated logarithm)
lnSC	The proportion of procurement value from the top five suppliers to the total annual procurement value (truncated logarithm)
lnNPM	The ratio of Net profit to operating receipt (logarithm truncated)
lnCR	The ratio of the sum of monetary funds and trading financial assets to current liabilities (truncated logarithm)
LnE/D	The ratio of the Total Owner's Equity to liabilities (truncated logarithm)
IV	The number of Ming Dynasty post stations in the prefecture-level cities where the enterprises are located.
Year	Year dummy variable

3.3 Model Specification

Because corporate default probability PD_{it} is left-censored (Left-censored), meaning some observations are compressed to zero, ordinary panel regression would yield biased estimates. Therefore, this study adopts the random-effects Tobit (RE-Tobit) model as the baseline estimation method. This model introduces random individual effects c_i to capture time-invariant firm heterogeneity and assumes that c_i is independent of the explanatory variables. The model specification is as follows.

$$PD_{it}^{*} = \beta_0 + \beta_1 lnSCCD_{it} + \gamma Controls_{it} + c_i + \mu_{it} \tag{1}$$

$$PD_{it} = \max(0, PD_{it}^{*}) \tag{2}$$

$$c_i | X_i \sim N(0, \sigma_c^2),\ \ \mu_{it} | X_i, c_i \sim N(0, \sigma_\mu^2) \tag{3}$$

where PD_{it}^{*} is the latent variable of corporate default probability; PD_{it} is the observed KMV default probability; $Controls_{it}$ is the vector of control variables; c_i is the random individual effect, $c_i \sim N(0,\sigma_c^2)$, which is independent of the explanatory variables; μ_{it} is the random disturbance term, $\mu_{it} \sim N(0,\sigma_\mu^2)$; σ_c^2 and σ_μ^2 are the variances of the individual effect and the random error, respectively.

4. Empirical Results

4.1 Baseline Regression Analysis

Table 3 reports the baseline regression results. Columns (1) and (2) present the pooled Tobit estimation results, while columns (3) and (4) present the random-effects Tobit (RE-Tobit) estimation results. The core explanatory variable lnSCCD exerts a significantly negative effect on the dependent variable in columns (1) and (3), and this result remains significant after control variables are included in columns (2) and (4). The RE-Tobit results in columns (3) and (4) indicate the presence of significant individual effects, rendering the RE-Tobit model superior to the pooled Tobit model. As a reference, the pooled Tobit results in columns (1) and (2) likewise support the reliability of the core conclusions.

Table 3 Baseline Regression Result

Model **DV**	**Tobit** **PD** **(1)**	**Tobit** **PD** **(2)**	**RE-Tobit** **PD** **(3)**	**RE-Tobit** **PD** **(4)**
lnSCCD	-0.0612*** (-18.22)	- 0.0224*** (-8.18)	-0.0577*** (-9.69)	-0.0351*** （ 6.36 ）
lnNPM		-0.0148 (-1.62)		-0.0600*** (-5.62)
lnCR		0.0213*** (13 .19)		0.0109*** (4.86)
lnE/D		-0.1799*** （ -76.71 ）		-0.1262*** (-30.57)
_cons	0.2953*** (19.85)	0. 2388*** （ 8.51 ）	0.1908*** (7.56)	0.2422*** （ 0.60 ）
VCE	robust	robust	Bootsrap	Bootsrap
Year FE	YES	YES	YES	YES
Id FE	NO	NO	NO	NO
Obvs	31561	31561	31561	31561
Left-censord	5	5	5	5
Right-censord	334	334	334	334
Log-likelihood	-4154.5221	2060.3482	4240.3146	6574.2564
wald	χ^2=2376.44 p=0.0000	χ^2=13411.75 p=0.0000	χ^2=2732.12 p=0.0000	χ^2=3707.80 p=0.0000
rho			0.5598	0.4194

Note: *, **, and *** indicate significance at the 10%,5%, and 1% levels, respectively; the values in parentheses are t/z values.

4.2 Mechanism Inspection Analysis

To reveal the micro-level transmission channels through which supply chain concentration affects default risk, this study decomposes supply chain concentration into customer concentration (LnCC) and supplier concentration (lnSC). Table 4 reports the RE-Tobit estimation results. Columns (1) and (2) show that customer concentration exerts a significantly negative effect on default risk; columns (3) and (4) show that supplier concentration likewise significantly reduces default risk. Both dimensions contribute to the risk mitigation effect, indicating that downstream demand stability and upstream supply security are complementary transmission mechanisms. As shown in the mechanism test results in Table 4, to reveal the transmission pathways through which supply chain digitalization affects default risk, this study employs the RE-Tobit model for mechanism testing, focusing on the mediating roles of supply chain concentration and supply chain stability.

Table 4 Mechanism Testing Results

Model DM	**RE-Tobit PD (1)**	**RE-Tobit PD (2)**	**RE-Tobit PD (3)**	**RE-Tobit PD (4)**
lnCC	-0.0356*** (-8.17)	-0.0226*** (-6.06)		
lnSC			-0.0398*** (-7.51)	-0.0238*** (-5.30)
_cons	0.1027*** (5.23)	0.1920*** (11.59)	0.1279*** (5.49)	0.2033*** (9.92)
Controls	NO	YES	NO	YES
Id Year	YES	YES	YES	YES
Id FE	NO	NO	NO	NO
VCE	Bootsrap	Bootsrap	Bootsrap	Bootsrap
Obvs	31561	31561	31561	31561
Left-censord	5	5	5	5
Right-censord	334	334	334	334
Log-likelihood	4212.9576	6567.8599	4196.5981	6551.9578
Wald	χ^2 = 2390.59 p=0.0000	χ^2= 3795.94 p= 0.0049	χ^2 = 2819.61 p=0.0000	χ^2 = 3766.95 p=0.0000
Rho	0.5602	0.4179	0.5603	0.4190

Note: *, **, and *** indicate significance at the 10%,5%, and 1% levels, respectively; the values in parentheses are t/z values.

4.3 Robustness Test

Table 5 reports the robustness test results. To ensure that our conclusions are not influenced by model specification or variable measurement, we conduct tests along two dimensions. First, we change the estimation method by replacing the RE-Tobit model with OLS. Second, we replace the dependent variable by substituting default probability PD with its logarithmic form lnPD. Columns (1) and (2) use PD as the dependent variable, while columns (3) and (4) use lnPD as the dependent variable. The core explanatory variable lnSCCD remains significantly negative across all columns, with significance at the 1% level in all cases. These results indicate that, regardless of whether linear estimation or logarithmic transformation is adopted, the risk-reducing effect of supply chain concentration on default risk remains stable, further corroborating the reliability of our baseline conclusions.

Table 5 Robustness test results

Model DM	**OLS PD (1)**	**OLS PD (2)**	**OLS lnPD (3)**	**OLS lnPD (4)**
lnSCCD	-0.0507*** (-6.63)	-0.0384*** (-5.60)	-0.2102*** (-6.93)	-0.15673*** (-5.86)
_cons	0.1584*** (5.26)	0.2182*** (8.05)	-2.7454*** (-21.21)	-2.4765*** (-21,71)
Controls	NO	YES	NO	YES
Year FE	YES	YES	YES	YES
Id FE	YES	YES	YES	YES
VCE	Robust	Robust	Robust	Robust
Obvs	31561	31561	31561	31561
R^2	0.1285	0.2036	0.1789	0.2391

Note: *, **, and *** indicate significance at the 10%,5%, and 1% levels, respectively; the values in parentheses are t/z values.

4.4 Endogenous Processing

Table 6 reports the endogeneity-corrected estimation results. To alleviate potential endogeneity bias arising from omitted variables and reverse causality, this study adopts the control function (CF) approach proposed by Blundell and Powell (2004). In the first stage, using the historical geographic variable, the number of Ming Dynasty post stations in the prefecture-level city where the firm is located, as the instrumental variable (IV), we regress the endogenous variable lnSCCD via OLS and extract the residual term denoted as Cf1. In the second stage, the residual term is incorporated into the RE-Tobit model for estimation.

First-stage results show that the instrumental variable exerts a significantly negative effect on lnSCCD, and the first-stage F-statistic is 29.14, far exceeding the Stock-Yogo weak instrument test critical value of 16.38, thereby rejecting the weak instrument hypothesis and satisfying the relevance requirement of the instrumental variable. Second-stage RE-Tobit-CF estimation shows that the coefficient on the core explanatory variable lnSCCD is significantly negative at the 5% level, and the first-stage residual term Cf1 is significantly positive, indicating that endogeneity indeed exists in the original baseline model. However, after correcting for the bias, the core conclusion that supply chain concentration reduces corporate default risk remains valid.

Table 6 Endogenousity test results

DV Model Stage	(1) lnSCCD OLS First stage	(2) PD RE-Tobit-CF Seconed stage
IV	-0.0028* (-2.77)	
lnSCCD		-0.7633* (-2.53)
Cf1		0.7283* (2.41)
_cons	3.4599*** (113.57)	2.7628* (2.64)
Controls	YES	YES
Year FE	YES	YES
Id FE	NO	NO
VCE	Robust	Bootstrap
Obvs	31561	31561
Left-censord		5
Right-censord		334
Log-likelihood		6577.1656
R^2/Wald	R^2=0.0226	χ^2 =9929.54
First-stage F	29 .14***	

Note: *, **, and *** indicate significance at the 10%,5%, and 1% levels, respectively; the values in parentheses are t/z values.

5. Conclusions

Based on data from Chinese A-share listed enterprises spanning 2001 to 2022, this study systematically examines the impact of supply chain concentration on listed company default risk. RE-Tobit estimation results indicate that elevated supply chain concentration significantly reduces corporate default probability, and this conclusion remains valid after OLS robustness tests and control function endogeneity correction. Mechanism analysis further reveals that both customer concentration and supplier concentration contribute to the risk mitigation effect, indicating that downstream demand stability and upstream supply security jointly guide firms in avoiding financial distress.

Based on these findings, this study proposes the following policy recommendations. For enterprises, they should prudently evaluate supply chain structure and establish long-term strategic cooperative relationships with core suppliers and major customers to balance efficiency and resilience. For regulators, they should strengthen supply chain information disclosure requirements for listed companies, particularly concentration data regarding top five customers and suppliers, enabling markets to timely identify potential supply chain risk contagion nodes. For financial institutions, they may incorporate supply chain concentration and its changing trends into corporate credit rating systems as auxiliary indicators for default risk early warning.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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