

Do Interlocking Networks Matter for Bank Loan Contracts? — —Evidence from Chinese Firms

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Abstract. This paper studies the effect of top management team (*TMT*) network centrality on bank loan contracts. We show that firms with high *TMT* network centrality obtain bank loans with lower loan spreads, longer loan maturity, and fewer collateral requirements. In addition, we consider the channels by which *TMT* network centrality influences loan spreads, because loan pricing is the key component in a loan contract that is largely based on risk. By using some proxy variables, we find that interlocking networks affect loan spreads by reducing agency costs, alleviating information asymmetry, expanding resource channels, and enhancing the reputation of companies. This paper expands the research on the economic consequences of interlocking networks and provides empirical evidence for capital markets regulation in emerging markets.

Keywords: top management team (*TMT*), interlocking networks, centrality, bank loan contracts.

1. Introduction

Bank debt financing has become a crucial source of external funding for companies globally, particularly in emerging economies like China, where the bond market remains underdeveloped, leading to a heavy reliance on bank loans for corporate financing [1]. The design and arrangement of bank loan contracts are essential in mitigating opportunistic behavior from debtors, alleviating agency conflicts between debtors and creditors, and reducing information asymmetry [2]. Given the unique role of bank loans in corporate financing, understanding the factors influencing bank loan contracts is a significant area of study [3].

Previous research has primarily focused on firm characteristics and corporate governance as determinants of bank loan contracts [4]. However, recent interdisciplinary studies have begun to explore the impact of social networks on these contracts. Social networks serve as an alternative mechanism to address institutional deficiencies, enabling firms to exchange information, build trust, and enhance their operational efficiency [5]. Specifically, corporate social networks formed through shared executives can help reduce market friction and agency problems, which leads to more favorable loan terms [6].

China's relational society, characterized by Confucian culture, emphasizes informal relationships over formal institutions, making it an ideal context for examining the influence of social networks on bank loans [7]. Many companies in China navigate a developing legal and financial system and often rely on social connections to facilitate financial transactions [8]. Interlocking networks, where executives serve on multiple boards, are prevalent, with studies indicating that approximately 93.13% of Chinese enterprises share executives [9]. Such networks can yield various advantages, including reduced earnings management, improved corporate governance, higher credit ratings, and enhanced innovation [10].

Conversely, some argue that interlocking networks may lead to negative outcomes, such as ineffective monitoring and increased earnings management, which can undermine corporate governance and firm value [11]. Given these conflicting perspectives, further investigation into the effects of interlocking networks within China's unique institutional context is warranted [12].

This study examines how interlocking networks influence bank loan contracts by analyzing the network centrality of top management teams (*TMT*), which includes CEOs, CFOs, board members, and other executives. The findings indicate that firms with high *TMT* network centrality enjoy more

favorable loan terms, such as lower spreads, longer maturities, and fewer collateral requirements [13]. This relationship remains robust after controlling for various factors. Additionally, the study identifies several channels through which TMT network centrality impacts loan pricing, including reduced agency costs, diminished information asymmetry, expanded resource access, and enhanced corporate reputation [14].

This paper contributes to the literature by expanding the analysis of social networks in corporate borrowing beyond financial and political connections to include interlocking networks, a topic gaining traction in economics and management [15]. Furthermore, it broadens the focus from specific executives to all TMT members, recognizing their collective contribution to a firm's social capital [16]. By constructing both unweighted and weighted networks for centrality metrics, this study offers a more comprehensive approach to understanding the dynamics of interlocking networks and their implications for bank loan contracts [17].

2. Research design

2.1. Sample selection and data source

The data used in this study includes TMT networks, bank loan information, and financial data, focusing on all A-shared listed firms in the Chinese stock market from January 1, 2010, to December 31, 2022. We obtained TMT member information for 4,960 firms from the WIND database, covering details such as name, gender, position, and education. To establish the TMT network, we created unique IDs for approximately 138,000 TMT members across the study period. Interlocking TMT members are defined as those working in two or more firms within a fiscal year. Since the executive information file only provides start and departure dates, we manually compiled the senior executives for each company annually. Using MATLAB, we constructed an adjacency matrix ($N \times N$) for each year based on firm linkages and calculated network centrality with UCINET and MATLAB. To ensure comparability of network centrality across years, we followed the method outlined by Qiu et al. [18] and normalized the annual data by the maximum value for that year, resulting in 42,734 observations of TMT network centrality.

We manually compiled bank loan information from the annual financial reports of firms listed in the WIND database, which includes loan announcement dates, loan spreads, loan sizes, loan maturities, and collateral status. We applied the following filtering criteria: (1) exclude financial companies; (2) omit firms lacking bank loan data; and (3) exclude firms labeled as ST or ST*. This process yielded an initial sample of 11,578 loan spread observations (2,305 firms), 28,342 loan maturity observations (3,069 firms), and 40,610 collateral requirement observations (3,597 firms).

Financial information was sourced from the CSMAR database. We merged the bank loan data and financial data with TMT network centrality observations, refining the final sample by removing (1) firms without TMT network centrality data and (2) firms with incomplete financial information. Additionally, we winsorized the data at 1% to mitigate the impact of outliers.

2.2. Measuring variables

2.2.1 Bank loan contracts

Following prior studies, we use loan spreads (*Spread*), loan maturity (*Maturity*), and security (*Security*) as proxies for loan contract terms. *Spread* is the difference between the annual interest rate charged by the lending bank and the benchmark rate issued by the People's Bank of China (PBOC, the central bank) (spread benchmark). *Maturity* is the actual term of a bank loan in months. *Security* is a dummy variable that takes a value of one if the loan is collateralized and zero otherwise.

2.2.2 The TMT network

Based on graph theory, we construct the entire network of all the A-shared listed firms each year, and the networks are considered to be undirected. We calculate both the unweighted and weighted

networks in this paper to more comprehensively and accurately investigate the role of the interlocking networks. For unweighted interlocking networks, the *Degree* centrality is measured as follows:

$$Degree_i = \sum_{i \neq j} A_{ij} / (n-1) \quad (1)$$

where A_{ij} is the adjacency matrix, when firm i and firm j have shared members, $A_{ij}=1$; otherwise $A_{ij}=0$, n is the network size. The greater the value of *Degree*, the greater the number of companies that have shared executives with firm i .

the *Betweenness* centrality is measured as follows:

$$Betweenness_i = \frac{\sum_{j \neq k} g_{jk}(n_i) / g_{jk}}{(n-1)(n-2) / 2} \quad (2)$$

where g_{jk} is the number of geodesics (a geodesic is the shortest path between two firms) linking firm j and firm k , $g_{jk}(n_i)$ is the number of geodesics linking firm j and firm k that pass through firm i , n is the network size. The greater the value of *Betweenness*, the more important the channel position occupied by firm i , and the stronger the influence of firm i on information flow.

the *Eigenvector* centrality is measured as follows:

$$Eigenvector_i = \frac{1}{\lambda} \sum_j A_{ij} e_j \quad (3)$$

where A_{ij} is the adjacency matrix, A_{ij} equals to 1 when firm i and firm j are linked, otherwise 0; e_j is an eigenvector of the adjacency matrix, and λ is the associated maximum eigenvalue, which is usually the largest eigenvalue of the adjacency matrix. The *Eigenvector* centrality measures the quality of firms' network relationships. That is, firms are considered central when they are directly linked to other well-connected firms.

Because *Degree*, *Betweenness* and *Eigenvector* centrality measures have multicollinearity problems, we perform principal component analysis and take the first principal component as the *Composite* centrality variable. *Composite* is a comprehensive measure for *Degree*, *Betweenness* and *Eigenvector*.

For weighted interlocking networks, the idea of calculating centrality is consistent with that of unweighted interlocking networks. The difference is, the adjacency matrix A_{ij} is changed from a binary matrix to a multi-valued matrix, where the numerical value represents the specific number of executives shared between the two companies. For example, when firm i and firm j have x number of shared members, $A_{ij}=x$; otherwise $A_{ij}=0$. The edges in the adjacency matrix are weighted numerically during the calculation of *Degree_w*, *Betweenness_w*, and *Eigenvector_w*. We also create the *Composite_w* centrality variable as the comprehensive measure for the three weighted centrality variable measures because of the collinearity problem.

2.3. Empirical analysis model

This study tests two hypotheses, we use Eq. (4) to test *Hypothesis 1* that examines how *TMT* network centrality affect bank loan terms.

$$\begin{aligned} Loan_Term_{it} = & \beta_0 + \beta_1 TMTNetworkCentrality_{it} + \beta_2 Size_{it} + \beta_3 Age_{it} \\ & + \beta_4 Leverage_{it} + \beta_5 ROE_{it} + \beta_6 BM_{it} + \beta_7 SOE_{it} + \beta_8 Duality_{it} + \beta_9 First_{it} \\ & + \beta_{10} Poid_{it} + \beta_{11} Loan_Concentration_{it} + IndustryDummies \\ & + YearDummies + \varepsilon_{it} \end{aligned} \quad (4)$$

The dependent variable, *Loan_Term*, includes *Spread*, *Log Maturity* and *Security*. The main independent variable, *TMT Network Centrality*, includes the unweighted network centrality (*Degree*, *Betweenness*, *Eigenvector*, and *Composite*), and weighted network centrality (*Degree_w*,

Betweenness_w, *Eigenvector_w*, and *Composite_w*). We use unweighted network centrality in the fundamental regression analyses, and use weighted network centrality in the robustness analyses.

In addition, we use firm characteristics (*Size*, *Age*, *Leverage*, *ROA*, *MTB*, *SOE*, *Big4*, *Duality*, *First*, *Poid*) and loan characteristic (*Loan_Conc*) as control variables, which have been shown to affect bank loan terms.

Second, Eqs. (4) - (6) are to test *Hypothesis 2*, which related to a formal mediation analysis. Eqs. (5) - (6) are specified as follows:

$$MediatorVariable_{it} = \alpha_0 + \alpha_1 TMTNetworkCentrality_{it} + \alpha_2 X_{it} + IndustryDummies + YearDummies + \varepsilon_{it} \tag{5}$$

$$Spread_{it} = \delta_0 + \delta_1 TMTNetworkCentrality_{it} + \delta_2 MediatorVariable_{it} + \delta_3 X_{it} + IndustryDummies + YearDummies + \varepsilon_{it} \tag{6}$$

Where *MediatorVariable* in Eq. (5) is the set of mediator variable that include the agency cost channel, the information channel, the resource channel, and the trust channel, separately.

3. Empirical results

Table 1 Descriptive statistics

Variable	Obs.	Mean	SD	P25	Median	P75
<i>Spread (%)</i>	9244	0.087	1.274	-0.540	0.000	0.650
<i>Loan_Size(RMB million)</i>	37579	502.203	996.741	50.000	150.000	472.971
<i>Maturity(months)</i>	23655	31.495	29.647	12.000	24.000	36.000
<i>Security</i>	34952	0.240	0.427	0.000	0.000	0.000
<i>Degree</i>	37579	0.292	0.231	0.077	0.231	0.462
<i>Betweenness</i>	37579	0.495	0.390	0.000	0.714	0.826
<i>Eigenvector</i>	37579	0.071	0.111	0.008	0.037	0.081
<i>Composite</i>	37579	0.000	0.239	-0.250	0.014	0.162
<i>Degree_w</i>	37579	0.169	0.139	0.042	0.125	0.250
<i>Betweenness_w</i>	37579	0.491	0.386	0.000	0.706	0.819
<i>Eigenvector_w</i>	37579	0.001	0.012	0.000	0.000	0.001
<i>Composite_w</i>	37579	0.000	0.114	-0.132	0.019	0.084
<i>Asset utilization ratio</i>	37241	0.600	0.479	0.303	0.498	0.752
<i>Internal control quality</i>	26343	1.977	0.639	2.000	2.000	2.000
<i>Media coverage</i>	36998	1.317	1.420	0.420	0.910	1.750
<i>Financial ties</i>	36875	4.585	5.571	1.000	3.000	7.000
<i>Political ties</i>	36875	5.534	6.315	1.000	4.000	8.000
<i>CSR_RKS</i>	9805	0.388	0.110	0.316	0.365	0.444
<i>CSR_HX</i>	33806	0.239	0.164	0.156	0.211	0.271
<i>Size</i>	37579	22.630	1.147	21.780	22.510	23.360
<i>Age</i>	37579	12.090	7.414	6.000	11.000	18.000
<i>Leverage</i>	37579	0.528	0.172	0.401	0.529	0.656
<i>ROA</i>	37579	0.025	0.055	0.010	0.026	0.048
<i>MTB</i>	37579	1.676	0.734	1.158	1.441	1.952
<i>SOE</i>	37579	0.388	0.487	0.000	0.000	1.000
<i>Big4</i>	37579	0.042	0.201	0.000	0.000	0.000
<i>Duality</i>	37579	0.265	0.441	0.000	0.000	1.000
<i>First</i>	37579	0.325	0.133	0.218	0.304	0.415
<i>Poid</i>	37579	0.374	0.051	0.333	0.364	0.429
<i>Loan_Conc</i>	37579	0.250	0.272	0.042	0.125	0.385

Table 1 provides the descriptive statistics of the main variables. The loan spreads (*Spread*) are under a mean (median) of 0.087% (0.000%) and vary from the first quartile of -0.540% to the third quartile of 0.650%. The mean (median) of loan maturity (*Maturity*) are 31.495 (24.000) months. The mean probability of security (*Security*) is 0.240, which implies that 24% of the loans have collateral requirements. For the unweighted network, the means of *Degree*, *Betweenness*, *Eigenvector*, and *Composite* centrality are 0.292, 0.495, 0.071, and 0.000, respectively. The weighted network mean values of *Degree_w*, *Betweenness_w*, *Eigenvector_w*, and *Composite_w* centrality are 0.169, 0.491, 0.001, and 0.000, respectively. The large difference in the mean value of each centrality variable indicates that different indicator measures can indeed reflect the different positions of firms in the network. Due to space constraints, the descriptive statistics results of other variables are not described here.

Another critical concern about endogeneity is the impact of *TMT* network centrality on bank loan contracts may be influenced by sample selection bias. In this paper, the propensity score matching method is used to address such concern. Since the PSM process requires an indicator variable to distinguish between treatment group samples and control group samples, we add the variable, *Link_executive*, to measure the *TMT* networks. *Link_executive* is an indicator that equal to one when there is at least one interlocking *TMT_executive* member in a firm, where *TMT_executive* is defined as CEOs, CFOs, and board members. Here, we limit members of the network to *TMT_executive* because they are the most important managers in a company. We match each treatment group (*Link_executive* is equal to one) to the control group (*Link_executive* is equal to zero) by the nearest neighborhood matching. Then we perform the baseline regression with matching observation data after PSM. Table 4 reports the regression results of matched samples. We can see that most of the centrality variables remain significantly negative with *Spread* and *Security*, while they have a significant positive relationship *Log Maturity*. Therefore, the results of PSM support our findings in Table 2.

Table 2 Robustness test using the PSM approach

	<i>Spread</i>				<i>Log Maturity</i>				<i>Security</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<i>Degree</i>	- 0.735 *** (- 6.010)				0.01 5* (0.98 0)				- 0.410 *** (- 3.880)			
<i>Betweenness</i>		- 0.524 *** (- 6.960)				0.01 6** (1.80 0)				- 0.210 *** (- 3.650)		
<i>Eigenvector</i>			- 2.38 7** (- 2.25 0)				0.04 8 (1.56 0)				- 0.35 8 (- 1.59 0)	
<i>Composite</i>				- 1.081 *** (- 9.040)				0.02 7*** (1.76 0)				- 0.415 *** (- 4.110)
<i>Control Variables</i>	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
<i>_cons</i>	1.476 * (1.95 0)	1.569 ** (2.09 0)	1.17 2 (1.5 80)	0.744 (0.99 0)	0.77 1*** (7.94 0)	0.77 3*** (7.99 0)	0.78 2*** (8.02 0)	0.79 2*** (8.07 0)	7.882 *** (11.8 80)	7.995 *** (12.0 90)	8.08 1*** (12.2 20)	7.729 *** (11.5 70)
<i>Year</i>	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
<i>Industry</i>	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
<i>N</i>	3404	3404	3404	3404	8216	8216	8216	8216	1360 5	1360 5	1360 5	1360 5
<i>Adj./ Pseudo R²</i>	0.289	0.293	0.31 1	0.305	0.13 5	0.13 5	0.13 5	0.13 5	0.087	0.087	0.08 6	0.087

4. Summary

This study examines how TMT network centrality affects bank loan contracts for publicly traded Chinese firms from January 1, 2010, to December 31, 2022. Our findings indicate that firms with higher TMT network centrality secure loans with more favorable terms, including lower spreads and longer maturities, while facing fewer collateral requirements. We provide robust support for these results through various methods, including 2SLS regression and PSM. Additionally, TMT network centrality influences loan terms by reducing agency costs and information asymmetry, enhancing credibility, and improving resource channels. Our work contributes to understanding the practical implications for investors and borrowing firms in managing debt risks.

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