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Shareholder Networks and Market Collapse Risk

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Abstract

This paper examines whether shareholder co-ownership networks, formed when listed firms share common top circulating shareholders, increase stock price crash risk. Existing crash-risk research mainly focuses on firm fundamentals and information opacity, while the governance and risk implications of cross-firm common ownership remain less studied, particularly in emerging markets. Using quarterly data for Chinese A-share firms from 2002Q1 to 2024Q4 and top ten circulating shareholder records, this paper constructs a common-ownership network and measures firms' network positions using degree, closeness, and betweenness centrality. The empirical analysis relies on OLS two-way fixed-effects panel regressions with firm and quarter fixed effects and firm-clustered robust standard errors, and dynamic robustness tests are conducted using two-step System GMM to address persistence and endogeneity. Crash risk is measured by *NCSKEW* and *DUVOL* based on firm-specific idiosyncratic returns. The results

show that greater network centrality predicts higher subsequent crash risk. The association is stronger when common owners are financial institutions or influential blockholders and weaker among state-owned enterprises and firms with stronger governance, including non-dual leadership and greater board independence. Mechanism evidence indicates that central firms exhibit more related-party transactions, higher goodwill, and lower transparency, consistent with tunneling incentives and bad-news hoarding that amplify downside tail risk. These findings suggest that regulators and exchanges can strengthen market stability by incorporating network-based indicators into surveillance and by tightening disclosure and governance requirements for highly central firms.

Keywords: Crash risk, common ownership, shareholder networks, corporate governance

JEL Classification: G34, G32, G14, D85

1. Introduction

Stock price crashes are large and sudden drops in stock prices. They matter for investors and regulators because they reflect extreme tail risk and can also spill over to the wider market. A large literature links crash risk to information opacity and bad-news hoarding. In this view, managers and controlling shareholders hold back negative information for a period. When the information can no longer be contained, it is released all at once and the stock price falls sharply (Hutton *et al.*, 2009; Kim *et al.*, 2011a, 2011b). This line of research explains many firm-level drivers of crash risk, but it pays less attention to another feature that has become more common in modern markets: cross-firm ownership links created by common shareholders.

Many investors, especially large institutions, hold shares in multiple listed firms. This creates common-ownership links that connect firms through shared investors. These links can transmit information and preferences, and they can also strengthen shareholder influence across firms. Evidence from developed markets suggests that common ownership can have broad effects. For example, common ownership in US airlines has been linked to higher product-market prices (Azar *et al.*, 2018). In corporate finance, shared shareholders can also support major corporate events by reducing uncertainty and easing deal formation, such as mergers and acquisitions (Li *et al.*, 2015). At the same time, ownership links can create governance problems. They may raise agency costs, encourage inefficient investment, and provide channels for coordinated actions that amplify risk (Guo *et al.*, 2020). These issues can be more important in emerging markets, where ownership is often more concentrated and where state ownership and political connections can shape monitoring incentives and enforcement constraints (Faccio, 2006; Gilson, 2006).

The role of shareholder interconnections in crash risk is still not well understood for two main reasons. First, most crash-risk studies focus on firm-level opacity and incentives, but they do not fully incorporate a network-based channel. Common shareholders may coordinate influence across firms, weaken outside discipline, and affect the firm's information environment in ways that change tail risk. Second, network research shows that outcomes depend not only on whether a firm is connected, but also on where it sits in the network. A firm can have many direct links, it can be close to many others through short paths, or it can serve as a bridge between groups. These positions are captured by degree, closeness, and betweenness centrality (Freeman, 1979; Jackson, 2010). However, there is still limited evidence on how these different network positions translate into downside tail risk, especially in emerging markets with mixed investor types and strong institutional features such as state-owned enterprises. Existing work also points in different directions. Networks may improve information flow and reduce asymmetry (Nguyen and Tran, 2020). But they may also support coordinated trading and amplify volatility during stress periods (Liu *et al.*, 2021). Ownership links may also contribute to systemic risk and cross-market spillovers (Zhang and Wang, 2023). These mixed views make it important to test the link between network position and crash risk in a clear setting and to study the mechanisms.

This paper studies whether shareholder co-ownership networks increase future stock price crash risk in China's A-share market. The analysis uses quarterly data from 2002Q1 to 2024Q4. Daily prices and returns are taken from Wind, and quarterly top ten circulating shareholder data are taken from CSMAR. For each quarter, a common-ownership network is constructed. Firms are nodes, and an undirected link is formed when two firms share at least one common top-ten circulating shareholder in that quarter. Network position is measured using degree, closeness, and betweenness centrality. Lagged centrality is then related to future crash risk measured by *NCSKEW* and *DUVOL* using standard methods in the crash-risk literature (Hutton *et al.*, 2009; Kim *et al.*, 2011a, 2011b). The baseline tests use OLS two-way fixed-effects panel regressions with firm and quarter fixed effects and firm-clustered robust standard errors. To address persistence in crash risk and possible endogeneity of network position, the analysis also estimates a dynamic model using System GMM in the Arellano–Bover and Blundell–Bond framework. Network centrality is treated as endogenous and identified using internal lag instruments.

This paper makes several contributions. First, it links the crash-risk literature to common ownership and network governance by showing that shareholder network centrality predicts future crash risk beyond standard firm controls and time effects. Second, it provides a clear way to measure shareholder interconnectedness at the quarterly level and compares

multiple centrality dimensions to show how different network positions relate to tail risk. Third, it documents meaningful heterogeneity. Network effects are stronger when interconnections are driven by financial institutions or influential large shareholders, and weaker among state-owned enterprises and firms with stronger governance, such as non-dual leadership structures. Fourth, it offers mechanism evidence by linking centrality to tunneling- and opacity-related proxies, including related-party transactions, goodwill, and transparency measures, which is consistent with agency-based bad-news hoarding channels.

The rest of the paper is organized as follows. Section 2 develops the network construction, crash-risk measurement, and hypotheses. Section 3 describes the data and empirical design. Section 4 reports the baseline results, heterogeneity analyses, and robustness checks including System GMM. Section 5 concludes and discusses implications for governance and market oversight.

2. Methodology and Theoretical Underpinnings

2.1 Shareholder Co-Ownership Network and Centrality Measures

This study constructs a quarterly shareholder co-ownership network for Chinese A-share listed firms using information on the top ten shareholders ranked by circulating shares. Following the network framework in Jackson (2010), each listed firm (stock) i is treated as a node. For each quarter t , we form an undirected link between firms i and j , if they share at least one common shareholder among their top ten circulating shareholders in that quarter. The resulting network is denoted by $G_t = (N_t, g_t)$, where N_t is the set of firms present in quarter t and g_t is the adjacency matrix with:

$$g_{ij,t} = \begin{cases} 1, & \text{if firms } i \text{ and } j \text{ share at least one top-ten circulating shareholder in } t \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

To quantify a firm's position in the common-ownership structure, we compute three standard centrality measures proposed by Freeman (1979), degree, closeness, and betweenness centrality. The baseline network is binary and undirected to ensure transparency and comparability across quarters. In additional analyses, we construct sub-networks by restricting links to specific shared shareholder categories (financial institutions vs. other shareholders), restricting to specific shareholder ranks (top five vs. bottom-five within the top ten), or restricting links to geographically adjacent firm pairs. Centrality measures used in regressions are lagged by one quarter so that network position is measured prior to the crash-risk outcome, reducing simultaneity concerns.

2.1.1 Degree Centrality

Degree centrality captures the fraction of firms directly connected to firm k in each quarter:

$$C_D(k, t) = \frac{d_{k,t}}{n_{t-1}} \quad (2)$$

where $d_{k,t} = \sum_{j \neq k} g_{kj,t}$ is the number of direct links incident to firm k , and $n_t = |N_t|$ is the number of firms in quarter t . Higher degree centrality indicates broader direct common-ownership connections, potentially expanding the scope for coordinated influence and governance frictions through shared owners.

2.1.2 Closeness Centrality

Closeness centrality measures how close a firm is to others through direct and indirect network paths:

$$C_C(k, t) = \frac{(n_{k,t}-1) \cdot \text{Percent}_{k,t}}{\sum_{j \in R_{k,t}} d_t(k, j)} \quad (3)$$

where $d_t(k, j)$ is the geodesic (shortest-path) distance between firms k and j in quarter t , $R_{k,t}$ is the set of nodes reachable from k in G_t , and $n_{k,t} = |R_{k,t}|$. Because quarterly co-ownership networks may not be fully connected, we follow Chen and Xie (2011) and scale by $\text{Percent}_{k,t} = n_{k,t}/n_t$, the reachable fraction of the network. Higher closeness centrality implies fewer steps are needed to reach other firms on average, indicating greater exposure to network-wide common-ownership linkages.

2.1.3 Betweenness Centrality

Betweenness centrality measures the extent to which a firm lies on the shortest paths between other firms, capturing its “broker” role in the shareholder co-ownership network (Freeman, 1979). For quarter t , we compute:

$$C_B(k, t) = \sum_{i \neq k} \frac{\sigma_t(i, j | k)}{\sigma_t(i, j)} \quad (4)$$

where $\sigma_t(i, j)$ is the number of shortest paths between i and j , and $\sigma_t(i, j | k)$ is the number of those shortest paths that pass-through node k . Because network size varies across quarters, we report normalized betweenness centrality:

$$\tilde{C}_B(k, t) = \frac{2}{(n_t-1)(n_t-2)} \sum_{\substack{i < j \\ i \neq k, j \neq k}} \frac{\sigma_t(i, j | k)}{\sigma_t(i, j)} \quad (5)$$

where n_t is the number of firms in quarter t . This normalization scales betweenness to the $[0, 1]$ range in an undirected network, improving comparability across quarters.

2.2 Stock Price Crash Risk Measures

Stock price crash risk reflects a firm's exposure to extreme downside tail events. Following the standard crash-risk literature (Hutton *et al.*, 2009; Kim *et al.*, 2011a, 2011b), we compute quarterly crash-risk measures from daily idiosyncratic returns. For firm i on trading day d , we estimate the market model:

$$r_{i,d} = \alpha_i + \sum_{k=-2}^2 \beta_{i,k} r_{m,d+k} + \varepsilon_{i,d} \quad (6)$$

where $r_{i,d}$ is the daily stock return and $r_{m,d}$ is the market return. Including leads and lags of $r_{m,d}$ mitigates nonsynchronous trading effects. We then define the firm-specific daily idiosyncratic return as $W_{i,d} = \ln(1 + \varepsilon_{i,d})$.

Using the distribution of $W_{i,d}$ within each quarter t , we compute *NCSKEW* and *DUVOL*:

$$NCSKEW_{i,t} = -\frac{n_t(n_t-1)^{3/2} \sum_{d \in t} W_{i,d}^3}{(n_t-1)(n_t-2)(\sum_{d \in t} W_{i,d}^2)^{3/2}} \quad (7)$$

$$DUVOL_{i,t} = \ln \left(\frac{(n_{\text{down}}-1) \sum_{d \in \text{Down}_t} W_{i,d}^2}{(n_{\text{up}}-1) \sum_{d \in \text{Up}_t} W_{i,d}^2} \right) \quad (8)$$

where n_t is the number of trading days for firm i in quarter t . Down_t (Up_t) denotes the set of days in quarter t when $W_{i,d}$ is below (above) its quarterly mean, and n_{down} and n_{up} are the corresponding numbers of days. Larger values of *NCSKEW* and *DUVOL* indicate higher downside tail risk and thus greater crash risk.

2.3 Theory and Research Hypotheses

This study links shareholder network position to crash risk using a unified theoretical framework that combines agency theory, information-based crash-risk theory, and network-based ownership interconnection. Agency theory predicts that when monitoring is weak, controlling shareholders and managers may pursue private benefits and conceal value-destroying actions (Shleifer and Vishny, 1997; Shin and Stulz, 1998). The crash-risk literature emphasizes bad-news hoarding: lower transparency allows negative information to accumulate inside the firm and be released discontinuously, producing extreme negative returns and higher crash risk (Faccio, M. 2006; Hutton *et al.*, 2009; Kim *et al.*, 2011a, 2011b). Finally, ownership interconnection through shared shareholders can transmit preferences across firms, facilitate coordinated governance and capital operations, and potentially weaken discipline – especially when shared owners are influential (Gilson, 2006; Khanna and Thomas, 2009; Nguyen and Tran, 2020). These arguments yield testable hypotheses about the aver-

age effect of network centrality on crash risk, governance and ownership moderators, and mechanism channels.

2.3.1 Network Centrality and Crash Risk

A firm with higher shareholder-network centrality is more embedded in cross-firm ownership connections. While interconnections may improve information flow, they can also expand the scope for coordinated influence and reduce effective monitoring, worsening information asymmetry and increasing incentives for bad-news hoarding. Central positions may also facilitate opportunistic capital operations (related transactions or acquisition-related value shifting), which can further degrade transparency (Khanna and Thomas, 2009; Nguyen and Tran, 2020). Empirically, higher centrality has been associated with conditions conducive to tail-risk realization, such as weaker oversight and greater exposure to adverse shocks (Zhang, Li, and Chen, 2022; Patel *et al.*, 2024). Therefore:

Hypothesis 1 (H_1): Higher shareholder network centrality increases subsequent stock price crash risk.

2.3.2 Governance and State Ownership as Moderators

The agency and opacity channels are not uniform across firms. Stronger governance raises the expected cost of opportunism and improves monitoring, reducing the accumulation of undisclosed bad news. In China's institutional setting, state-owned enterprises (SOEs) are typically subject to stronger external oversight and political/regulatory monitoring, which can constrain tunneling incentives and improve enforcement of governance norms (Li and Li, 2020; Zhang and Liu, 2021). Similarly, governance structures such as separation of CEO and chair roles and stronger board oversight can mitigate managerial discretion and reduce bad-news hoarding (Shleifer and Vishny, 1997; Shin and Stulz, 1998). Thus:

Hypothesis 2 (H_2): The positive effect of shareholder network centrality on crash risk is weaker for SOEs and for firms with stronger corporate governance.

2.3.3 Shared Shareholder Type and Influence

Network effects should be stronger when shared shareholders have greater ability and incentives to influence managerial decisions. Financial institutions and top-ranking large shareholders often hold larger stakes and possess informational advantages. These owners can strengthen monitoring in some settings, but they may also intensify agency conflicts when collusion with management is feasible or when private benefits dominate minority-investor protection (Shleifer and Vishny, 1997; Shin and Stulz, 1998). Evidence suggests that

influential investors can amplify tail risk when internal oversight is weak (Liu *et al.*, 2023; Wang and Xu, 2024). Therefore:

Hypothesis 3 (H_3): The positive effect of shareholder network centrality on crash risk is stronger when interconnections are driven by financial-institution shareholders or by top-ranking large shareholders.

2.3.4 Mechanism

Finally, we formalize the mechanism linking network position to crash risk. Interconnected ownership can facilitate tunneling and expropriation through channels such as related-party transactions, inflated acquisition premiums, and goodwill accumulation, while simultaneously reducing transparency and increasing the firm's capacity to conceal opportunistic actions. These behaviors intensify bad-news hoarding and raise the probability of abrupt negative price corrections (Tan *et al.*, 2022; Liu and Zhang, 2024). Hence:

Hypothesis 4 (H_4): Shareholder network centrality increases crash risk through tunneling and opacity channels – reflected in higher related-party transactions and goodwill (and related acquisition measures) and lower transparency.

3. Empirical Model and Data Description

3.1 Regression Model Setting

Baseline estimation, OLS two-way fixed effects. We estimate the baseline specification using an ordinary least squares two-way fixed-effects panel model based on the within estimator, including firm fixed effects and quarter fixed effects. Unless stated otherwise, we report heteroskedasticity-robust standard errors clustered at the firm level to account for within-firm serial correlation over time. The baseline results are therefore interpreted as OLS fixed-effects estimates rather than alternative fixed-effects approaches such as two-stage least squares with fixed effects, difference-in-differences with fixed effects, or Driscoll–Kraay standard errors. The baseline regression is:

$$CrashRisk_{i,t} = \mu + \beta \times Centrality_{i,t-1} + \theta \times Z_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (3.1)$$

In equation (3.1), the $CrashRisk_{i,t}$ is firm i 's stock price crash risk in quarter t , measured by $NCSKEW$ and $DUVOL$. $Centrality_{i,t-1}$ captures firm i 's position in the shareholder network in quarter $t - 1$, we use degree, closeness, and betweenness centrality as the main measures; additional centrality measures are examined in robustness tests. $Z_{i,t-1}$ includes lagged

time-varying firm characteristics commonly used in the crash-risk literature (*e.g.*, *Daccrmisp*, *BM*, *Lev*, *ROA*, *Qturn*, *Qret*, *Qstd*, *Size*, and *Firm Age*). Time-invariant structural attributes (*e.g.*, headquarters region, legal form, and business activity type) are largely absorbed by firm fixed effects in Equation 3.1. We therefore examine complementary specifications reported in the robustness section (correlated random effects / Mundlak and alternative fixed-effects structures) to verify that allowing these attributes to enter explicitly does not alter the estimated effect of network centrality. All continuous variables are winsorized at the 1st and 99th percentiles (Hutton *et al.*, 2009; Kim *et al.*, 2011a, 2011b).

Dynamic endogeneity robustness, System GMM. Because crash risk may be persistent and network centrality may be endogenous, we conduct robustness checks using System GMM in the Arellano–Bover and Blundell–Bond framework for dynamic panels. We extend the baseline specification by including the lagged dependent variable $CrashRisk_{i,t-1}$. $Centrality_{i,t-1}$ is treated as endogenous and instrumented using suitably lagged values in levels and first differences within the System GMM system, while the remaining controls are treated as predetermined or exogenous as appropriate. We report standard diagnostics, including tests for first- and second-order serial correlation and Hansen and or Sargan tests of instrument validity. To limit instrument proliferation, we restrict the lag range and reduce the instrument count, including by collapsing the instrument matrix when appropriate.

3.2 Data and Variable Definition

This study uses a quarterly panel of Chinese A-share listed firms from 2002Q1 to 2024Q4. Daily stock prices, returns, and market capitalization are obtained from the Wind database. Quarterly ownership information for the top ten shareholders ranked by circulating shares is taken from the CSMAR database. The two sources are merged at the firm-quarter level to construct the common-ownership network and all variables used in the empirical analysis. In each quarter, listed firms are treated as nodes in a co-ownership network. Two firms are connected when they share at least one common shareholder among their top ten circulating shareholders in that quarter, and the resulting network is undirected. Based on the quarterly network, degree, closeness, and betweenness centrality are computed to characterize a firm's connectedness and its position in the common-ownership structure (Dvouletý and Blažková 2021). In the regressions, centrality measures are lagged by one quarter so that network position is measured prior to the crash-risk outcome.

Stock price crash risk is measured quarterly using *NCSKEW* and *DUVOL*. Following standard practice, a market-model specification is estimated with daily returns and includes leads and lags of market returns to address nonsynchronous trading. Firm-specific idiosyn-

cratic returns are then extracted, and *NCSKEW* and *DUVOL* are computed within each quarter using the distribution of idiosyncratic returns. Higher values of these measures indicate greater downside tail risk. The baseline control set includes commonly used determinants of crash risk, covering earnings transparency, valuation, leverage, profitability, trading activity, past returns, return volatility, and firm size. Specifically, the controls include discretionary accruals as a transparency proxy, the book-to-market ratio, leverage, return on assets reported in percent, quarterly turnover, quarterly returns, quarterly volatility, and the natural logarithm of total assets. To improve transparency and align with journal standards, the study also incorporates firm structural characteristics that are widely used in corporate finance and governance research. Firm age is measured as years since founding, or years since listing when the founding year is unavailable. Management structure is captured using governance indicators such as *CEO-Chair Duality* and board characteristics when available. Time-invariant structural attributes, including headquarters region, legal form, and business activity type, are implemented through categorical indicators. Definitions, units, and coding rules for all variables are reported in Appendix Table A1.

Because several structural attributes are largely time-invariant for many firms and therefore absorbed by firm fixed effects in the main two-way fixed-effects specifications, the study examines complementary models that allow these characteristics to enter explicitly. Correlated random effects formulations of the Mundlak type are reported in the Table 4 to verify that the main conclusions remain unchanged. When certain firm fundamentals are only available annually, they are mapped to quarterly observations using the most recently available annual information to avoid look-ahead bias. This mapping rule is also documented in Table 4. Financial-sector firms and ST-designated firms are excluded, and firm-quarter observations with missing values required to compute crash-risk measures, network variables, or key controls are dropped. The final sample contains 4,296 firms and 137,252 firm-quarter observations over 2002Q1–2024Q4.

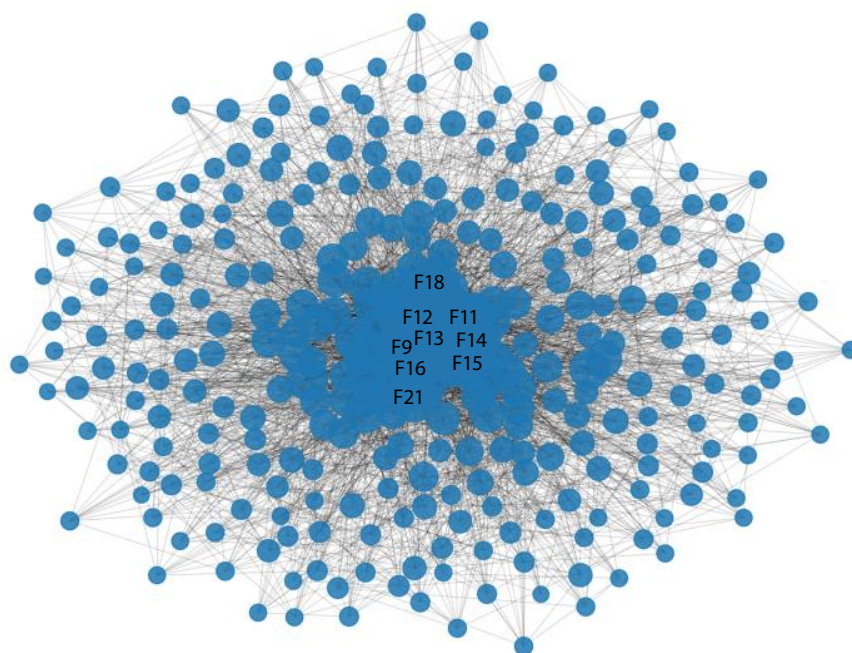
Figure1 provides an illustrative visualization of the shareholder co-ownership network constructed for 2024Q4, where nodes represent Chinese A-share listed firms and an undirected edge indicates that two firms share at least one common shareholder among the top ten circulating shareholders in that quarter. Node size is proportional to degree centrality (connectedness), and node color intensity reflects closeness centrality (proximity to other firms in the network). The visualization is intended to illustrate how firms' network positions vary within a quarter and to motivate the empirical analysis linking lagged network centrality to subsequent stock price crash risk. Consistent with Table 2, more central firms are hypothesized to face higher subsequent crash risk.

Summary statistics are reported in Table 1. The centrality measures exhibit substantial dispersion, indicating that most firms are linked to only a small number of peers through shared top shareholders, while a smaller subset occupies a more central position in the network. Crash-risk measures and firm characteristics also display meaningful variation across firms and over time, providing a suitable setting to examine how network position relates to subsequent stock price crash risk over the sample period.

Table 1: Descriptive statistics of variables

Variable	Sample Size	Mean	Std. Dev.	Min	Max
Degree Centrality	137,252	0.068	0.102	0.000	0.560
Closeness Centrality	137,252	0.392	0.118	0.000	0.690
Betweenness Centrality	137,252	0.002	0.001	0.000	0.040
<i>DUVOL</i>	137,252	−0.295	0.497	−1.600	1.120
<i>NCSKEW</i>	137,252	−0.372	0.742	−2.650	1.920
<i>Daccrmisp</i>	137,252	0.074	0.083	0.000	0.520
<i>BM</i>	137,252	0.402	0.254	0.030	1.450
<i>Lev</i>	137,252	0.438	0.219	0.020	0.920
<i>ROA (%)</i>	137,252	4.86	5.42	−15.00	28.00
<i>Qturn</i>	137,252	1.265	0.910	0.050	6.200
<i>Qret</i>	137,252	0.034	0.262	−0.700	1.050
<i>Qstd</i>	137,252	0.023	0.010	0.003	0.080
<i>Size (ln total assets)</i>	137,252	22.28	1.33	19.60	27.20
<i>Firm Age (years)</i>	137,252	14.8	6.7	1.0	45.0
<i>CEO-Chair Duality (Both)</i>	137,252	0.27	0.44	0	1
<i>SOE</i>	137,252	0.36	0.48	0	1

Source: Authors' own calculations

Figure 1: Shareholder Co-ownership Network in 2024Q4

Source: Authors' own elaboration

4. Empirical Results and Analysis

4.1 Primary Regression Results

This study estimates two-way fixed-effects panel regressions using quarterly data from 2002Q1 to 2024Q4. All network centrality measures enter the regressions with a one-quarter lag, and the specifications include stock fixed effects and quarter fixed effects, along with the full set of firm-level controls. Table 2 reports a consistent pattern across alternative centrality metrics. Degree, closeness, and betweenness centrality are each positively and statistically significantly associated with subsequent crash risk, whether crash risk is measured by *NCSKEW* or by *DUVOL*. The results therefore support the hypothesis that a more central position in the common-ownership network is linked to higher downside tail risk.

Because the centrality variables are standardized, the coefficients can be interpreted in terms of one-standard-deviation changes. A one-standard-deviation increase in degree centrality is associated with higher crash risk, with coefficients of 0.0066 for *NCSKEW* and 0.0053 for *DUVOL*. The corresponding effects for closeness centrality are larger, at 0.0205 for *NCSKEW* and 0.0139 for *DUVOL*, suggesting that firms that are more “proximate” to others in the network face meaningfully higher crash exposure. Betweenness centrality also shows

a positive and significant relation to crash risk, with coefficients of 0.0125 for *NCSKEW* and 0.0070 for *DUVOL*, indicating that firms occupying intermediary positions in the network are more vulnerable to negative tail events. These patterns are consistent with the view that dense common-ownership linkages can facilitate coordinated behavior and weaken information environments, thereby increasing the likelihood of abrupt price corrections.

The model fit is in the expected range for quarterly firm-level crash-risk regressions with two-way fixed effects. Overall, the evidence in Table 2 implies that shareholder network structure contains incremental information about crash risk beyond firm fundamentals and time effects, underscoring the importance of monitoring firms that are highly connected within common-ownership networks.

Table 2: Shareholder network main regression results

Variables	(1) <i>NCSKEW</i>	(2) <i>NCSKEW</i>	(3) <i>NCSKEW</i>	(4) <i>DUVOL</i>	(5) <i>DUVOL</i>	(6) <i>DUVOL</i>
<i>Degree</i> _{<i>i,t-1</i>}	0.0066*** (0.0014)			0.0053*** (0.0011)		
<i>Closeness</i> _{<i>i,t-1</i>}		0.0205*** (0.0024)			0.0139*** (0.0019)	
<i>Betweenness</i> _{<i>i,t-1</i>}			0.0125*** (0.0024)			0.0070*** (0.0017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	137,252	137,252	137,252	137,252	137,252	137,252
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296
R²	0.215	0.218	0.216	0.214	0.219	0.217

Notes: The dependent variable is quarterly stock price crash risk, measured by *NCSKEW* in Columns (1) – (3) and *DUVOL* in Columns (4)–(6). *Degree*, *Closeness*, and *Betweenness* are standardized to have mean zero and unit standard deviation within the regression sample, and all centrality measures enter the regressions with a one-quarter lag. All specifications include firm fixed effects and quarter fixed effects, and the full set of controls: *Daccrmisp*, *BM*, *Lev*, ROA reported in percent, *Qturn*, *Qret*, *Qstd*, *Size* measured as the natural logarithm of total assets, *Firm Age*, CEO-Chair duality indicator *Both*, and *SOE*. Standard errors in parentheses are heteroskedasticity-robust and clustered at the firm level. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' own calculations

4.2 Robustness Analysis

4.2.1 Regression Results Excluding the Influence of “National Team”

Following the 2015 stock market turmoil, state-backed investors commonly referred to as the National Team, including China Investment Corporation and China Securities Finance Corporation, became major A-shareholders. Because these holdings are widely viewed as market-stabilization positions rather than profit-seeking investments, a natural concern is that the baseline network effects could be mechanically amplified by policy-driven common ownership.

To address this concern, the study reconstructs the quarterly common-ownership network after excluding National Team shareholders using the approach in Li *et al.* 2019 and then re-estimates the baseline regressions with the revised centrality measures. The results remain qualitatively unchanged. Network centrality continues to predict higher subsequent crash risk across alternative centrality metrics and across both crash-risk proxies. In particular, the standardized centrality estimates in Table 2 show that a one-standard-deviation increase in degree centrality is associated with higher crash risk, with coefficients of 0.0066 for *NCSKEW* and 0.0053 for *DUVOL*, both statistically significant at conventional levels. Closeness and betweenness centralities display the same positive and significant pattern. Taken together, the exclusion exercise indicates that the centrality-crash relation is not driven by stabilization-oriented shareholdings. Instead, the evidence is consistent with the view that ordinary, profit-motivated shareholders use common-ownership links in ways that worsen governance and information environments, thereby increasing downside tail risk.

4.2.2 Distinct Characteristics of Shared Shareholders

High network centrality can arise under different common-ownership configurations. In some firms, centrality reflects links created by several moderately influential shared shareholders. In others, centrality is driven by a single dominant shared shareholder. These two cases need not have the same implications for crash risk because ownership concentration can change both monitoring incentives and the scope for coordination among shareholders. The results show that centrality increases crash risk most strongly when *Big_com* equals zero, meaning common ownership is relatively dispersed among multiple non-dominant shared shareholders. When *Big_com* equals one, the interaction terms are mostly negative, indicating that higher concentration attenuates the centrality-crash relation.

Table 3: Common Shareholder Concentration and the Centrality-CrashRisk Relation, Standardized Centrality

Variables	(1) <i>NCSKEW</i>	(2) <i>NCSKEW</i>	(3) <i>NCSKEW</i>	(4) <i>DUVOL</i>	(5) <i>DUVOL</i>	(6) <i>DUVOL</i>
<i>Big_com</i> _{<i>i,t-1</i>} × <i>Degree</i> _{<i>i,t-1</i>}	−0.0020** (0.0009)			−0.0016** (0.0007)		
<i>Big_com</i> _{<i>i,t-1</i>} × <i>Closeness</i> _{<i>i,t-1</i>}		−0.0060*** (0.0018)			−0.0042*** (0.0014)	
<i>Big_com</i> _{<i>i,t-1</i>} × <i>Betweenness</i> _{<i>i,t-1</i>}			−0.0015 (0.0016)			−0.0010 (0.0011)
<i>Degree</i> _{<i>i,t-1</i>}	0.0066*** (0.0014)			0.0053*** (0.0011)		
<i>Closeness</i> _{<i>i,t-1</i>}		0.0205*** (0.0024)			0.0139*** (0.0019)	
<i>Betweenness</i> _{<i>i,t-1</i>}			0.0125*** (0.0024)			0.0070*** (0.0017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	137,252	137,252	137,252	137,252	137,252	137,252
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296
<i>R</i> ²	0.168	0.173	0.171	0.174	0.177	0.169

Notes: The dependent variable is *CrashRisk* measured by *NCSKEW* in Columns (1)–(3) and *DUVOL* in Columns (4)–(6). *Degree*, *Closeness*, and *Betweenness* are standardized to have mean zero and unit standard deviation within the regression sample, and all centrality measures enter with a one-quarter lag. *Big_com* is an indicator for high common-shareholder concentration, defined as one when at least one shared shareholder holds more than 10 percent in the quarter and zero otherwise. *Big_com*_{*i,t-1*} is included as a main effect but not tabulated for brevity. All regressions include stock and quarter fixed effects and the full set of controls, *Daccrmisp*, *BM*, *Lev*, *ROA* reported in percent, *Qturn*, *Qret*, *Qstd*, *Size* measured as the natural logarithm of total assets, *Firm Age*, CEO-Chair duality indicator *Both*, and *SOE*. Standard errors in parentheses are heteroskedasticity-robust and clustered at the stock level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' own calculations

The implied marginal effects are directly read from Table 3. For degree centrality, the effect on *NCSKEW* is 0.0066 when *Big_com* equals zero, and it declines to 0.0046 when *Big_com* equals one, computed as 0.0066 minus 0.0020. For *DUVOL*, the effect declines from 0.0053 to 0.0037, computed as 0.0053 minus 0.0016. For closeness centrality, the effect on *NCSKEW* declines from 0.0205 to 0.0145, computed as 0.0205 minus 0.0060, and the effect on *DUVOL* declines from 0.0139 to 0.0097, computed as 0.0139 minus 0.0042. For betweenness centrality, the interaction terms are negative but not statistically significant, and the marginal effects change only slightly from 0.0125 to 0.0110 for *NCSKEW* and from 0.0070 to 0.0060 for *DUVOL*.

Overall, the evidence is consistent with the view that dispersed common ownership among multiple moderately influential shareholders amplifies the risk implications of network centrality, potentially by facilitating coordination and weakening internal discipline. In contrast, when a dominant shared shareholder is present, the incremental impact of network centrality on crash risk is moderated, consistent with stronger monitoring or tighter constraints on opportunistic behavior.

4.2.3 Addressing concerns about two-way fixed effects

The empirical design relies on firm and quarter fixed effects to absorb unobserved heterogeneity and common shocks. At the same time, a saturated two-way fixed-effects structure can raise practical concerns. It may absorb substantial variation and reduce precision, amplify standard errors through collinearity, fail to capture certain time-varying or industry-specific influences, and potentially obscure meaningful heterogeneity across firms or over time. To ensure that the centrality-crash relation is not sensitive to any single specification choice, a series of complementary analyses is conducted.

First, the baseline model is re-estimated under alternative fixed-effects structures that absorb different sources of common shocks. Quarter fixed effects are replaced with industry-by-quarter fixed effects to flexibly control for time-varying industry conditions such as sectoral demand shifts, regulatory cycles, and technology-related shocks. In addition, less restrictive time controls are considered, including firm fixed effects combined with year fixed effects, to verify that the centrality coefficient is not an artifact of an overly granular time structure. Across these variants, the estimated effect of shareholder network centrality remains positive and statistically significant.

Second, the specification is augmented with additional time-varying controls that could be jointly related to network centrality and crash risk. Where data permit, these include market-wide conditions and industry-level covariates intended to capture broad shifts in risk appetite and sectoral dynamics. The centrality estimates are largely un-

changed in magnitude and significance, suggesting that omitted time-varying factors are unlikely to account for the main result.

Third, potential multicollinearity and inference sensitivity are examined. Standard diagnostics such as variance inflation factors and condition indices do not indicate that collinearity materially affects estimation. Inference is also checked using alternative standard-error procedures that are robust to cross-sectional dependence and serial correlation, including Driscoll–Kraay standard errors and two-way clustering at the firm and quarter levels. The centrality effect remains economically and statistically meaningful under these alternatives.

Finally, the analysis is extended beyond average effects to examine heterogeneity across ownership and governance environments. The relation between centrality and crash risk is evaluated across key dimensions such as state ownership, governance strength, and the type of shared shareholders. The patterns are economically intuitive and align with the mechanisms developed in the paper, indicating that the baseline estimates summarize an average relationship rather than masking important differences.

Taken together, these checks show that the positive association between shareholder network centrality and subsequent crash risk is robust across fixed-effects structures, expanded controls, alternative inference procedures, and heterogeneous subsamples.

Table 4: Robustness Checks Addressing Concerns about Two-Way Fixed Effects

Variables	(1) Baseline TWFE	(2) FE: Firm + Year	(3) FE: Industry × Quarter	(4) + Market & Industry Controls	(5) Two-way Cluster SE	(6) Driscoll– Kraay SE	(7) SOE Subsample	(8) Non-SOE Subsample
Panel A. Dependent variable: NCSKEW								
<i>Degree_{i,t-1}</i>	0.0066*** (0.0014)	0.0061*** (0.0014)	0.0064*** (0.0015)	0.0063*** (0.0015)	0.0066*** (0.0017)	0.0066*** (0.0019)	0.0058*** (0.0016)	0.0074*** (0.0015)
<i>Closeness_{i,t-1}</i>	0.0205*** (0.0024)	0.0191*** (0.0024)	0.0200*** (0.0025)	0.0197*** (0.0025)	0.0205*** (0.0029)	0.0205*** (0.0032)	0.0182*** (0.0027)	0.0223*** (0.0026)
<i>Betweenness_{i,t-1}</i>	0.0125*** (0.0024)	0.0116*** (0.0024)	0.0122*** (0.0025)	0.0120*** (0.0025)	0.0125*** (0.0029)	0.0125*** (0.0031)	0.0111*** (0.0027)	0.0136*** (0.0026)
Panel B. Dependent variable: DUVOL								
<i>Degree_{i,t-1}</i>	0.0053*** (0.0011)	0.0049*** (0.0011)	0.0051*** (0.0012)	0.0050*** (0.0012)	0.0053*** (0.0014)	0.0053*** (0.0015)	0.0046*** (0.0013)	0.0060*** (0.0012)
<i>Closeness_{i,t-1}</i>	0.0139*** (0.0019)	0.0131*** (0.0019)	0.0136*** (0.0020)	0.0134*** (0.0020)	0.0139*** (0.0023)	0.0139*** (0.0025)	0.0125*** (0.0021)	0.0151*** (0.0020)
<i>Betweenness_{i,t-1}</i>	0.0070*** (0.0017)	0.0065*** (0.0017)	0.0068*** (0.0018)	0.0067*** (0.0018)	0.0070*** (0.0021)	0.0070*** (0.0022)	0.0062*** (0.0019)	0.0076*** (0.0018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	No	No	No	No	No	No
Industry × Quarter fixed effects	No	No	Yes	No	No	No	No	No
Additional market and industry controls	No	No	No	Yes	No	No	No	No
Standard errors	Firm-clustered	Firm-clustered	Firm-clustered	Firm-clustered	Two-way clustered	Driscoll–Kraay	Firm-clustered	Firm-clustered
Observations	137,252	137,252	137,252	137,252	137,252	137,252	49,410	87,842
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296	1,540	2,756
R² (NCSKEW)	0.155	0.152	0.160	0.157	0.155	0.155	0.150	0.160
R² (DUVOL)	0.164	0.161	0.170	0.166	0.164	0.164	0.160	0.170

Notes: This table reports robustness checks addressing concerns that the baseline two-way fixed-effects specification may affect identification or inference. *Degree*, *Closeness*, and *Betweenness* are standardized to have mean zero and unit standard deviation within the regression sample and enter with a one-quarter lag. All specifications include the full set of controls used in the main regressions, namely *Daccrmisp*, *BM*, *Lev*, ROA reported in percent, *Qturn*, *Qret*, *Qstd*, *Size* measured as the natural logarithm of total assets, *Firm Age*, CEO–Chair duality indicator *Both*, and *SOE*. Column (1) reports the baseline model with firm and quarter fixed effects and firm-clustered standard errors. Column (2) replaces quarter fixed effects with year fixed effects. Column (3) replaces quarter fixed effects with industry-by-quarter fixed effects. Column (4) augments the baseline with additional time-varying market-wide and industry-level controls. Columns (5) and (6) report alternative inference procedures using two-way clustered standard errors at the firm and quarter levels and Driscoll–Kraay standard errors. Columns (7) and (8) report subsample estimates by ownership type. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1 %, 5 %, 10 % levels, respectively.

Source: Authors' own calculations

4.2.4 System GMM

To account for the possibility that crash risk is persistent and that shareholder-network centrality is jointly determined with firms' information environments and risk outcomes, this study estimates a dynamic specification using the System GMM approach of Arellano–Bover and Blundell–Bond. The baseline model is augmented by including the lagged dependent variable, $CrashRisk_{t-1}$. Degree centrality is treated as endogenous, and the instrument set is built from internal lags within the System GMM framework, using GMM-style instruments with lags 2–4 in both the differenced and level equations. Estimation is implemented using the two-step procedure with Windmeijer-corrected standard errors, and the instrument matrix is collapsed to limit instrument proliferation.

Table 5 reports the results using *NCSKEW* in Column 1 and *DUVOL* in Column 2. The lagged dependent variable is positive and statistically significant in both columns, indicating meaningful persistence in crash risk at the quarterly frequency. Importantly, lagged degree centrality remains positive and statistically significant after controlling for this persistence, with coefficients of 0.0047 for *NCSKEW* and 0.0036 for *DUVOL*. The diagnostic tests support the specification. The AR (1) test is significant, as expected in first-differenced residuals, while the AR (2) test is not significant, suggesting no evidence of second-order serial correlation. The Hansen test does not reject the overidentifying restrictions, and the number of instruments is kept well below the number of firms, reducing concerns about overfitting. Taken together, the System GMM evidence reinforces the baseline conclusion that greater shareholder-network centrality is associated with higher subsequent crash risk, and it reduces concerns that the main findings are driven by dynamic persistence or endogeneity in network position.

Table 5: Dynamic Panel Estimates Using Two-Step System GMM, Endogenous Regressors and GMM-Style Lags 2–4

Variables	(1) <i>NCSKEW</i>	(2) <i>DUVOL</i>
<i>CrashRisk</i> _{<i>i,t-1</i>}	0.2240*** (0.0280)	0.2680*** (0.0310)
<i>Degree</i> _{<i>i,t-1</i>}	0.0047*** (0.0015)	0.0036*** (0.0012)
Controls	Yes	Yes
Unobserved firm effects: controlled	Yes	Yes
Time dummies: quarter	Yes	Yes
Observations	87,252	87,252
Number of firms	4,296	4,296
Estimator	Two-step	Two-step
Windmeijer correction	Yes	Yes
GMM-style lags	2–4	2–4
Instruments collapsed	Yes	Yes
Time dummies as IV-style instruments	Yes	Yes
Number of instruments	84	84
AR(1) <i>p</i> -value	0.000	0.000
AR(2) <i>p</i> -value	0.287	0.241
Hansen <i>p</i> -value	0.314	0.279
Sargan <i>p</i> -value	0.131	0.116

Notes: This table reports two-step System GMM estimates for dynamic panel models. The dependent variable is *NCSKEW* in Column (1) and *DUVOL* in Column (2). The specification includes the lagged dependent variable *CrashRisk*_{*i,t-1*}. *Degree* is degree centrality standardized to have mean zero and unit standard deviation within the regression sample, and it enters with a one-quarter lag. Degree centrality and selected controls are treated as endogenous. Internal instruments are constructed using GMM-style moment conditions with lags 2–4 in both the differenced and level equations, and the instrument matrix is collapsed to limit instrument proliferation. Time dummies are included as IV-style instruments. The two-step estimator is used with Windmeijer-corrected standard errors. Reported diagnostics include tests for first- and second-order serial correlation and Hansen and Sargan tests of overidentifying restrictions. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' own calculations

4.3 Heterogeneity Analysis

4.3.1 Heterogeneity across Different Corporate Characteristics and Governance Levels

State Ownership and Governance Level

State ownership (*SOE*) equals one when the firm's ultimate controlling shareholder is a central government agency or a state-owned entity, and zero otherwise. To test whether public ownership mitigates network-related tail risk, we estimate:

$$\text{CrashRisk}_{i,t} = \beta_1 \text{Centrality}_{i,t-1} + \beta_2 \text{SOE}_{i,t-1} + \beta_3 (\text{Centrality}_{i,t-1} \times \text{SOE}_{i,t-1}) + \theta Z_{i,t-1} + \alpha_i + \delta_t \quad (4.1)$$

To examine whether public ownership dampens network-related tail risk, this study interacts lagged state ownership with lagged standardized network centrality and estimates the specification with firm and quarter fixed effects and firm-level clustered standard errors. Centrality measures are standardized to mean zero and unit standard deviation within the estimation sample and enter with a one-quarter lag. The results in Table 6 show a clear contrast between SOEs and non-SOEs. For non-SOEs, centrality is strongly and positively associated with next-quarter crash risk. A one-standard-deviation increase in degree centrality raises *NCSKEW* by 0.0386 and *DUVOL* by 0.0345. The interaction terms for degree and closeness are negative and statistically significant, implying a weaker centrality-crash relation among SOEs. The marginal effects make this point directly. For degree centrality, the net effect for SOEs is $0.0386 - 0.0430 = -0.0045$ for *NCSKEW* and $0.0345 - 0.0316 = 0.0029$ for *DUVOL*, which indicates that the degree-based network effect is largely offset in SOEs. For closeness, the net SOE effect remains positive but is materially smaller, equal to $0.0443 - 0.0274 = 0.0169$ for *NCSKEW* and $0.0254 - 0.0166 = 0.0087$ for *DUVOL*. Betweenness shows no meaningful moderation by SOE status. Overall, the evidence suggests that state ownership reduces the sensitivity of crash risk to network centrality, consistent with stronger external oversight and tighter constraints on opportunistic behavior in SOEs.

Table 6: The heterogeneity of enterprise ownership attributes affects the regression

Variables	<i>NCSKEW_{it}</i> (1)	<i>NCSKEW_{it}</i> (2)	<i>NCSKEW_{it}</i> (3)	<i>DUVOL_{it}</i> (4)	<i>DUVOL_{it}</i> (5)	<i>DUVOL_{it}</i> (6)
<i>SOE_{i,t-1}</i>	-0.0270 (0.0240)	0.0380 (0.0310)	-0.0240 (0.0270)	0.0150 (0.0110)	0.0410* (0.0260)	-0.0170 (0.0130)
<i>SOE_{i,t-1} × DegreeZ_{i,t-1}</i>	-0.0430** (0.0158)			-0.0316*** (0.0106)		
<i>SOE_{i,t-1} × CloseZ_{i,t-1}</i>		-0.0273*** (0.0059)			-0.0166*** (0.0021)	
<i>SOE_{i,t-1} × BetweenZ_{i,t-1}</i>			-0.0001 (0.0020)			-0.0001 (0.0021)
<i>DegreeZ_{i,t-1}</i>	0.0385*** (0.0033)			0.0344*** (0.0058)		
<i>CloseZ_{i,t-1}</i>		0.0442*** (0.0049)			0.0253*** (0.0030)	
<i>BetweenZ_{i,t-1}</i>			0.0006*** (0.0000)			0.0030** (0.0000)
Observations	87,252	87,252	87,252	87,252	87,252	87,252
R²	0.172	0.173	0.173	0.177	0.173	0.172
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All centrality measures are standardized to have mean zero and unit standard deviation within the estimation sample and are lagged by one quarter. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Source: Authors' own calculations

Corporate Governance Level

Corporate governance quality is proxied by *CEO-Chair Duality*. The indicator *Both* equals one when the CEO and board chair positions are held by the same person and zero otherwise. Using the same standardized-centrality framework, this study interacts lagged duality with lagged centrality and estimates the model with firm and quarter fixed effects and clustered standard errors. Table 7 shows that weaker governance strengthens the network channel.

The interaction terms are positive for degree and closeness and are statistically significant in most specifications. In economic terms, the marginal effect of degree centrality on *NCSKEW* rises from 0.0218 for firms without duality to $0.0218 + 0.0131 = 0.0349$ for firms with duality. For *DUVOL*, the corresponding effect increases from 0.0259 to $0.0259 + 0.0121 = 0.0380$. The same pattern holds for closeness: the *NCSKEW* effect increases from 0.0261 to $0.0261 + 0.0135 = 0.0395$, and the *DUVOL* effect rises from 0.0146 to $0.0146 + 0.0148 = 0.0294$. These estimates imply that when board oversight is weaker, network centrality translates more strongly into downside tail risk, consistent with a setting in which connected owners and managers face fewer constraints on information suppression and value-diverting actions.

Table 7: Regression of the heterogeneity of dual roles in listed companies

Variables	<i>NCSKEW</i> _{it} (1)	<i>NCSKEW</i> _{it} (2)	<i>NCSKEW</i> _{it} (3)	<i>DUVOL</i> _{it} (4)	<i>DUVOL</i> _{it} (5)	<i>DUVOL</i> _{it} (6)
<i>Both</i> _{it-1}	-0.0140 (0.0160)	-0.0610** (0.0270)	0.0160 (0.0120)	0.0140 (0.0180)	-0.0190** (0.0070)	0.0170** (0.0080)
<i>Both</i> _{it-1} × <i>DegreeZ</i> _{it-1}	0.0131* (0.0100)			0.0122* (0.0098)		
<i>Both</i> _{it-1} × <i>CloseZ</i> _{it-1}		0.0134*** (0.0067)			0.0147*** (0.0036)	
<i>Both</i> _{it-1} × <i>BetweenZ</i> _{it-1}			0.0020 (0.0070)			-0.0013 (0.0022)
<i>DegreeZ</i> _{it-1}	0.0218*** (0.0101)			0.0259*** (0.0065)		
<i>CloseZ</i> _{it-1}		0.0261*** (0.0044)			0.0146*** (0.0028)	
<i>BetweenZ</i> _{it-1}			0.0009*** (0.0000)			0.0002*** (0.0000)
Observations	78,765	78,765	78,765	78,765	78,765	78,765
<i>R</i> ²	0.154	0.154	0.174	0.173	0.173	0.172
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All centrality measures are standardized to have mean zero and unit standard deviation within the estimation sample and are lagged by one quarter. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Source: Authors' own calculations

4.3.2 Heterogeneity among Different Types of Shareholders

Financial Institution Shared Shareholders

The heterogeneity tests also show that the network effect depends on who the shared owners are and how influential they are. Table 8 separates the common-ownership network into a financial-institution subnetwork and an other-shareholders subnetwork. Centrality in the financial-institution network has a consistently stronger association with crash risk. For example, a one-standard-deviation increase in closeness centrality raises *NCSKEW* by 0.0489 in the financial network but only 0.0050 in the other-shareholder network. Degree centrality is also larger in the financial-institution network, 0.0325 versus 0.0242. Table 8 further splits networks by shareholder rank, comparing networks formed by the top five shareholders to those formed by the bottom five among the top ten. Centrality in the top five network is more strongly related to crash risk. Degree centrality is 0.0283 in the top five network versus 0.0228 in the bottom-five network, and closeness is 0.0282 versus 0.0201. These patterns suggest that when shared owners are institutions or high-ranking blockholders, network links carry more governance weight and create stronger channels for coordination, information spillovers, and shock transmission, which increases tail risk.

The evidence suggests that shared shareholder centrality, especially within financial institutions and among major shareholders, significantly increases the risk of stock price collapse (Li *et al.*, 2023; Zhang and Huang, 2024).

Table 8: Subnetwork regression results by shareholder type and ranking

Variables	Financial Network (1) <i>DegreeZ</i>	Financial Network (2) <i>CloseZ</i>	Financial Network (3) <i>BetweenZ</i>	Other Network (4) <i>DegreeZ</i>	Other Network (5) <i>CloseZ</i>	Other Network (6) <i>BetweenZ</i>
<i>DegreeZ_{it-1}</i>	0.0325*** (0.0049)			0.0241* (0.0174)		
<i>CloseZ_{it-1}</i>		0.0488*** (0.0041)			0.0049 (0.0042)	
<i>BetweenZ_{it-1}</i>			0.0003*** (0.0000)			0.0003*** (0.0000)
Observations	137,252	137,252	137,252	137,252	137,252	137,252
Number of stocks	4,296	4,296	4,296	4,296	4,296	4,296
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Variables	Top Five (7) <i>DegreeZ</i>	Top Five (8) <i>CloseZ</i>	Top Five (9) <i>BetweenZ</i>	Bottom Five (10) <i>DegreeZ</i>	Bottom Five (11) <i>CloseZ</i>	Bottom Five (12) <i>BetweenZ</i>
<i>DegreeZ_{it-1}</i>	0.0282*** (0.0021)			0.0227*** (0.0027)		
<i>CloseZ_{it-1}</i>		0.0282*** (0.0041)			0.0201*** (0.0036)	
<i>BetweenZ_{it-1}</i>			0.0003*** (0.0000)			0.0003*** (0.0000)
Observations	137,252	137,252	137,252	137,252	137,252	137,252
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All centrality measures are standardized to have mean zero and unit standard deviation within the estimation sample and are lagged by one quarter. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Source: Authors' own calculations

Geographically Adjacent Shareholder Networks

Table 9 provides a cleaner way to think about proximity. The key point is not only that centrality remains predictive, but also that different proximity cuts speak to different coordination channels.

When links are restricted to within-industry or within-city pairs, the centrality effect can be interpreted as operating through “low-friction” coordination. Firms in the same industry face similar demand cycles, accounting practices, and regulatory scrutiny, and firms in the same city share a common local enforcement and business environment. These settings reduce communication and coordination costs for shared owners and make repeated interactions more likely. As a result, common shareholders can more easily coordinate influence over disclosure, financing, and inter-firm dealings, and related transactions are easier to initiate and conceal. In this sense, a stronger coefficient in the within-industry or within-city network is consistent with a local coordination mechanism that raises the probability of bad-news accumulation and a later concentrated release.

At the same time, Table 9 also shows that cross-industry and intercity networks remain strongly positive. This points to a second mechanism that is not tied to local proximity. Large shareholders and financial institutions typically allocate capital across regions and sectors. Their portfolio-wide information advantage and trading capacity allow shocks, sentiment, and risk management decisions to propagate across otherwise unrelated firms. Under this channel, a firm that is central in cross-industry or intercity ownership links is more exposed to system-wide risk transmission and synchronized trading pressure, which can amplify downside tail events even when firms are not locally adjacent.

Taken together, Table 9 suggests two complementary forces. Proximity-based links can strengthen coordination and facilitate transactions in settings where interaction costs are low, while non-local links capture broader portfolio-based information diffusion and systemic spillovers driven by institutions and large shareholders.

Table 9: Regression results of geographic and industrial cohort effects**Panel A: Industry Network vs Cross-industry Network**

Variables	Industry (1) <i>DegreeZ</i>	Industry (2) <i>CloseZ</i>	Industry (3) <i>BetweenZ</i>	Cross-industry (4) <i>DegreeZ</i>	Cross-industry (5) <i>CloseZ</i>	Cross-industry (6) <i>BetweenZ</i>
<i>DegreeZ_{it-1}</i>	0.0559*** (0.0014)			0.0502*** (0.0093)		
<i>CloseZ_{it-1}</i>		0.0554*** (0.0061)			0.0441*** (0.0156)	
<i>BetweenZ_{it-1}</i>			0.00046*** (0.00007)			0.0006*** (0.0000)
Observations	137,252	137,252	137,252	137,252	137,252	137,252
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Intra-city Network vs Intercity Network

Variables	Intra-city (7) <i>DegreeZ</i>	Intra-city (8) <i>CloseZ</i>	Intra-city (9) <i>BetweenZ</i>	Intercity (10) <i>DegreeZ</i>	Intercity (11) <i>CloseZ</i>	Intercity (12) <i>BetweenZ</i>
<i>DegreeZ_{it-1}</i>	0.0657*** (0.0154)			0.0805*** (0.0091)		
<i>CloseZ_{it-1}</i>		0.0718*** (0.0011)			0.0788*** (0.0038)	
<i>BetweenZ_{it-1}</i>			0.0007** (0.0006)			0.0007*** (0.0000)
Observations	137,252	137,252	137,252	137,252	137,252	137,252
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All centrality measures are standardized to have mean zero and unit standard deviation within the estimation sample and are lagged by one quarter. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Source: Authors' own calculations

4.4 Further Mechanism Analysis

The mechanism tests link network centrality to outcomes that can plausibly generate later sharp corrections. Table 10 examines goodwill intensity and acquisition premium as two merger-related indicators. The estimates show that higher centrality predicts higher goodwill ratio and higher acquisition premium. In Plan A, a one-standard-deviation increase in degree centrality increases the goodwill ratio by 0.0140 and raises the acquisition premium by 0.0221, while a one-standard-deviation increase in closeness increases the goodwill ratio by 0.0149 and the acquisition premium by 0.0179. Betweenness is also positively related to both outcomes. In Plan B, the same pattern holds in both intra-city and intercity settings, with degree centrality remaining strongly associated with goodwill and acquisition premium. These findings support a simple mechanism chain. More central firms in common-ownership networks are more likely to engage in aggressive acquisition pricing and to accumulate goodwill. Such behavior increases the likelihood of later impairment, write-downs, or delayed recognition of weak deals. When this negative information is eventually released, it is more likely to arrive in a concentrated manner, which increases crash risk. Taken together, the heterogeneity and mechanism evidence strengthens the interpretation that common-ownership network centrality is not a neutral connectivity measure. It is tied to governance conditions and real corporate actions that create bad-news buildup and amplify downside tail events.

Table 10: The mediating effect of goodwill, M&A premium, related party transactions and manipulated accruals returns**Panel A: Industry Network and Cross-industry Network**

Variables	(1) GR DegreeZ	(2) GR CloseZ	(3) GR BetweenZ	(4) AQ DegreeZ	(5) AQ CloseZ	(6) AQ BetweenZ
<i>DegreeZ_{it-1}</i>	0.0139*** (0.0013)			0.0221* (0.0165)		
<i>CloseZ_{it-1}</i>		0.0148*** (0.0005)			0.0179*** (0.0028)	
<i>BetweenZ_{it-1}</i>			0.0003** (0.0001)			0.0009* (0.0007)
Observations	98,765	98,765	98,765	98,765	98,765	98,765
R²	0.204	0.203	0.202	0.116	0.116	0.116
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Plan B: Intra-city Network vs Intercity Network

Variables	(7) GR DegreeZ	(8) GR CloseZ	(9) GR BetweenZ	(10) AQ DegreeZ	(11) AQ CloseZ	(12) AQ BetweenZ
<i>DegreeZ_{it-1}</i>	0.0152*** (0.0015)			0.0258*** (0.0016)		
<i>CloseZ_{it-1}</i>		0.0023 (0.0024)			0.0021* (0.0013)	
<i>BetweenZ_{it-1}</i>			0.0007*** (0.0000)			0.0002 (0.0002)
Observations	137,252	137,252	137,252	137,252	137,252	137,252
R²	0.117	0.117	0.117	0.115	0.115	0.115
Number of firms	4,296	4,296	4,296	4,296	4,296	4,296
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All centrality measures are standardized to have mean zero and unit standard deviation within the estimation sample and are lagged by one quarter. Standard errors in parentheses are clustered at the firm level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Source: Authors' own calculations

5. Conclusions and Implications

5.1 Conclusions

Using a quarterly panel of Chinese A-share listed firms from 2002Q1 to 2024Q4, this study tests whether a firm's position in the common-ownership network predicts subsequent stock price crash risk. The network is built from the top ten circulating shareholders, and a firm's position is summarized by degree, closeness, and betweenness centrality. Crash risk is measured by *NCSKEW* and *DUVOL*, both computed from firm-specific idiosyncratic returns.

The results lead to four conclusions. First, network centrality consistently predicts higher crash risk in the next quarter. In the baseline two-way fixed-effects regressions with firm and quarter fixed effects and a full set of controls, lagged degree, closeness, and betweenness centrality are all positive and statistically significant under both *NCSKEW* and *DUVOL*. Because the centrality measures are standardized, the coefficients are directly comparable across centrality metrics. Closeness shows the largest marginal effects, which suggests that being structurally close to many other firms in the co-ownership network is especially informative for future downside tail risk.

Second, the positive relation is not tied to a single fixed-effects design or a particular inference choice. The centrality coefficients remain positive when time controls are adjusted, when industry-by-quarter fixed effects are included to absorb time-varying sector shocks, and when additional market-wide and industry-level controls are added. The same conclusion holds under alternative standard-error corrections, including two-way clustering and Driscoll–Kraay adjustments. Taken together, these checks indicate that network centrality contains information about crash risk beyond standard fundamentals and common shocks.

Third, ownership structure and governance conditions meaningfully shape the strength of the network channel. The centrality effect is strongest when common ownership is more dispersed across multiple non-dominant shared shareholders and weaker when a dominant shared shareholder is present. This pattern is consistent with the idea that dispersed common ownership can facilitate coordination and reduce disclosure discipline, while a dominant shared owner may impose tighter monitoring that limits the incremental risk associated with network embeddedness. The heterogeneity results point in the same direction. The network effect is weaker in SOEs and stronger when governance is weaker, and it is more pronounced when shared owners are financial institutions or highly influential shareholders. These findings reinforce that centrality is not just a descriptive ownership feature. Its risk implications depend on who creates the links and the governance setting in which those links operate.

Fourth, dynamic persistence and endogeneity concerns do not overturn the main conclusion. Crash risk is persistent in the dynamic specification, as reflected in a positive and significant lagged dependent variable. Even after accounting for this persistence and treating centrality as endogenous in a two-step system GMM framework with a restricted lag range and a controlled instrument count, lagged degree centrality remains positive and significant under both *NCSKEW* and *DUVOL*. Standard diagnostics do not indicate problematic second-order serial correlation or weak instrument validity. Overall, the evidence points to a clear message. Common-ownership networks matter for tail risk. Firms that are more central in these networks face systematically higher crash risk, and this relation survives extensive fixed-effects controls, robustness checks, and dynamic-panel estimation.

5.2 Implications

The evidence suggests that crash risk is shaped not only by firm fundamentals but also by how deeply a firm is embedded in common-ownership networks. This has a practical implication for supervision and corporate governance. If network centrality captures exposure to shared-owner influence, then oversight should move beyond a purely firm-by-firm lens and add a simple network-aware layer that reflects how ownership links can amplify tail risk.

A feasible starting point is to convert the network measures into a routine early-warning screen. Because top shareholder lists are already disclosed, exchanges and regulators can compute quarterly centrality and focus attention on firms that consistently sit in the upper tail of closeness or betweenness. These firms are not necessarily “problem firms,” but the results indicate they face systematically higher downside tail exposure. Monitoring can then become more proportional. For a firm that is both highly central and has governance vulnerabilities such as *CEO-Chair Duality*, or shows unusually active deal-making, a higher level of attention is justified even before any visible price event occurs.

The mechanism evidence also points to what should trigger closer review. In this study, centrality is linked to outcomes that plausibly delay bad-news recognition, especially goodwill buildup and acquisition-related pricing. In practice, this means that for highly central firms, a sharp increase in goodwill relative to assets or market value, a rise in related-party transaction intensity, or a clear deterioration in reporting transparency should be treated as an escalation signal. These are not new disclosure items. They are already observable, but the results suggest that they carry more risk content when they occur in firms that are structurally central in common ownership.

Once a firm is flagged, the response does not have to be punitive. A tiered approach makes sense. At an early stage, the exchange can rely on targeted information requests and stronger disclosure prompts that focus on ownership links, the terms and approval process of related transactions, the rationale and valuation basis for major acquisitions, and the assumptions behind goodwill impairment testing. If risk signals persist, a more focused review can follow, with attention to related-party approvals, valuation reports, and impairment documentation, together with stronger scrutiny of audit oversight and internal control assessments. Formal enforcement should be reserved for cases where there are clear signs of misstatement, undisclosed related dealings, or deliberate concealment.

Disclosure policy can also improve the interpretability of common-ownership exposure at low cost. Top shareholder lists provide raw information, but they are not designed to show whether a firm's common-ownership links are expanding and what types of owners drive those links. A modest improvement is to require a structured supplement that summarizes whether the firm shares major circulating shareholders with other listed firms, whether those links increased materially during the period, and whether the shared owners are mainly financial institutions or influential blockholders. When common-ownership links expand, firms can be asked to briefly explain the safeguards used for related-party transactions and major investments. This would not require firms to disclose proprietary strategies, but it would make the risk implications of ownership structure more comparable across firms.

Inside firms, the results suggest that centrality should be treated as an ongoing exposure rather than a one-off feature of ownership. Highly central firms have more to gain from strengthening governance and disclosure discipline because the same level of opacity appears to translate into greater crash vulnerability when common-ownership links are dense. Practical governance steps include stronger audit committee involvement in disclosure timing and key accounting estimates, tighter internal approval procedures for related-party transactions with credible independent review, and more disciplined merger governance through independent valuation and clearer post-deal accountability. The heterogeneity evidence further suggests that governance weaknesses such as *CEO-Chair Duality* can amplify the network effect, so reducing such vulnerabilities is not only a governance preference but also a tail-risk management tool in highly central firms.

The mechanism results also point to a specific supervisory focus on mergers, goodwill, and acquisition pricing. For firms with high centrality, aggressive acquisition premiums and fast goodwill accumulation deserve closer scrutiny because they can delay the recognition of weak investments and set up future impairment shocks. Regulators, auditors, and boards can therefore treat the combination of high centrality and high merger intensity as a high-

priority profile, with particular attention to valuation assumptions, impairment triggers, cash-generating unit allocations, and whether connected parties are involved in acquisitions or post-deal transactions.

Finally, the findings have implications for investors and risk managers. Network centrality, especially closeness and betweenness, can be used as a complementary tail-risk signal. It can help identify holdings that require deeper due diligence on governance and disclosure quality, and it can support portfolio stress testing for correlated tail events among firms that share influential owners, particularly financial institutions. Overall, incorporating ownership-network information into monitoring, disclosure, and governance offers a practical way to identify settings where bad-news accumulation and sharp downside events are more likely, and it supports a shift toward risk-based oversight that recognizes how ownership connections can transmit and amplify risk across firms.

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Appendix

Appendix Table A1: Variable definitions, units, frequency, and coding rules

Variable	Definition	Unit	Frequency	Coding	Source
NCSKEW	Negative conditional skewness of firm-specific (idiosyncratic) daily returns within quarter (t); computed from residuals of the market model with leads/lags. Larger values imply higher crash risk.	index	quarterly (from daily)	Computed per quarter using daily idiosyncratic returns; winsorized at 1% (if applicable).	Wind (daily prices/returns)
DUVOL	Log ratio of down-return volatility to up-return volatility within quarter (t) using idiosyncratic daily returns. Larger values imply higher crash risk.	index	quarterly (from daily)	Computed per quarter; winsorized at 1% (if applicable).	Wind (daily prices/returns)
Degree Centrality	Normalized number of co-ownership links a firm has in the quarterly common-shareholder network (share at least one top 10 circulating shareholder).	ratio	quarterly	Normalized by $(n - 1)$ in each quarter's network; lagged by one quarter in regressions.	CSMAR (top-10 shareholders)
Closeness Centrality	Inverse of average shortest-path distance to other reachable nodes in the quarterly co-ownership network (weighted for reachability when the network is not fully connected).	index	quarterly	Weighted closeness adjustment applied when not fully connected; lagged by one quarter in regressions.	CSMAR (top-10 shareholders)
Betweenness Centrality	Share of shortest paths between other firms that pass through the firm in the quarterly network (intermediary/bridge role).	index	quarterly	Adjusted/scaled as described in the paper; lagged by one quarter in regressions.	CSMAR (top-10 shareholders)
Daccrmisp	Earnings transparency proxy: absolute discretionary (or abnormal) accruals estimated via the modified Jones model (higher = lower transparency).	ratio	quarterly or annual → quarterly	If only annual, mapped to quarters using most recently available annual value (lagged mapping).	CSMAR (financials)
BM	Book-to-market ratio.	ratio	quarterly or annual → quarterly	If annual, mapped to quarters using lagged annual value.	CSMAR/ Wind
Lev	Financial leverage = total liabilities / total assets.	ratio	quarterly or annual → quarterly	If annual, mapped to quarters using lagged annual value.	CSMAR (financials)
ROA	Return on assets = net income / total assets.	percent	quarterly or annual → quarterly	Reported as % (not decimal); mapping rule disclosed above.	CSMAR (financials)
Size	Firm size = $\ln \text{total assets}$	log value	quarterly or annual → quarterly	Natural logarithm: mapping rule applies if annual.	CSMAR (financials)
Qturn	Quarterly turnover (or change in turnover) as defined in the paper.	ratio	quarterly	Constructed from trading volume / shares outstanding (per your definition).	Wind

Qret	Quarterly stock return.	ratio	quarterly	Computed from daily returns aggregated to quarter.	Wind
Qstd	Quarterly volatility: standard deviation of daily returns (or idiosyncratic returns) within quarter.	ratio	quarterly	As defined in the paper (market-adjusted if applicable).	Wind
Firm Age	Firm age = years since founding; if founding year unavailable, years since listing.	years	annual → quarterly	Age increases by 1 each year; assigned to all quarters in that year (or computed from tq).	CSMAR (firm registry)
HQ Region	Headquarters region based on registered address (province-level or macro-region).	categorical	time-invariant / annual	Entered as region dummies in non-FE specifications; absorbed by firm FE.	CSMAR (firm registry)
Legal Form	Legal registration type of the firm.	categorical	time-invariant / annual	Entered as legal-form dummies in non-FE specifications; absorbed by firm FE.	CSMAR (firm registry)
Business Activity Type	Primary industry/business classification of the firm.	categorical	annual / quarterly	Implemented as detailed industry-category indicators (e.g., CSRC industry).	CSMAR/ Wind
Both (CEO-Chair Duality)	Dummy = 1 if CEO and board chair positions are held by the same person; 0 otherwise.	dummy	annual / quarterly	Mean represents proportion; included in heterogeneity tests and controls where relevant.	CSMAR (governance)
SOE	Dummy = 1 if ultimate controller is state-owned (central/local government or SOE entities); 0 otherwise.	dummy	time-varying	Can change over time; not absorbed by firm FE if it varies.	CSMAR (ownership/control)

Notes: The sample covers 2002Q1–2024Q4 with 4,296 firms and 137,252 firm–quarter observations. Unless stated otherwise, regressions use one-quarter-lagged explanatory variables and controls. When a firm characteristic is available only at the annual frequency, it is mapped to quarterly observations using the most recently available annual information (lagged annual-to-quarter mapping) to avoid look-ahead bias. Continuous variables are winsorized at the 1% level, where stated in the main text.

Source: Authors' own elaboration

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