Geopolitical Risk and Corporate Debt Financing Costs: The Transmission Role of Supply Chain Uncertainty——Evidence from U.S.–China Trade Frictions and Chinese A-Share Listed Firms

Jia Dai
School of Management, Cranfield University, Bedfordshire, MK43 0AL, United Kingdom
Yilia.DJ.132@gmail.com

ABSTRACT

This paper examines whether the 2018 escalation of U.S.–China trade frictions increased the debt financing costs of Chinese listed firms and whether supply chain uncertainty mediates that effect. Using a continuous-treatment DID design on 41,675 Chinese A-share firm-year observations from 2010 to 2024, I interact firms' pre-shock overseas-sales exposure with a post-2018 indicator. Firms with higher exposure experienced larger increases in borrowing costs after the shock ($\beta = 0.014$, $p < 0.01$), equal to about 14 basis points for each 10-percentage-point increase in exposure. Event-study estimates show no differential pre-trends and that the effects are concentrated in 2018–2020. The shock also increases supply chain uncertainty ($\beta = 0.009$, $p < 0.01$), and the Sobel test indicates a statistically significant but economically modest mediation effect ($z = 2.406$, $p = 0.016$). The effect is larger in non-state-owned firms, financially constrained firms, and firms with weaker supply chain resilience. Overall, the evidence suggests that a specific geopolitical trade shock can affect debt pricing through firm-level operational instability.

Keywords: Geopolitical risk; Cost of debt; Supply chain uncertainty; Continuous DID; U.S.-China trade frictions; JEL Classification: F13, G32, L14, D81

1. INTRODUCTION

Geopolitical risk has become a persistent source of firm-level uncertainty in international production, sourcing, and financing networks [1]. Trade-policy uncertainty affects contracting, investment, and procurement decisions [2]. Although previous studies have shown that geopolitical risk increases financing frictions and the cost of capital [3,4], the firm-level channels through which such shocks affect debt pricing remain unclear.

This paper treats the 2017–2018 escalation of U.S.–China trade frictions as a quasi-natural experiment. It examines whether Chinese listed firms with higher ex ante overseas-sales exposure faced higher debt financing costs after the shock and whether supply chain uncertainty mediated that effect. This setting is appropriate because trade frictions affect both firms' operating conditions and access to external finance [5,6]. If trade tensions undermine supplier-customer relations and increase the uncertainty of procurement and sales networks, creditors may demand a higher risk premium [6,8,9].

Using a panel of Chinese A-share listed firms from 2010 to 2024, this paper estimates a continuous-treatment DID model that interacts pre-shock overseas-sales exposure with a post-2018 indicator. The results show that firms with higher exposure experienced larger increases in debt financing costs after the shock. The mediation effect through supply chain uncertainty is statistically significant but economically modest. The effect is larger in non-state-owned firms, financially constrained firms, and firms with weaker supply chain resilience. Overall, the evidence suggests that a specific geopolitical trade shock can raise debt financing costs, with SCU serving as one statistically significant but economically modest transmission channel.

2. LITERATURE REVIEW

2.1 Geopolitical risk, trade policy uncertainty, and debt financing

Higher geopolitical risk is associated with a higher cost of capital [3], tighter bank-loan contracting [4], and a higher cost of debt [10] when information asymmetry is more severe. Trade-policy uncertainty is particularly important in the U.S.–China context because it alters expected market access, contractual terms, and exposure to external demand [2]. Research on trade wars also shows that trade tensions have worsened financing conditions and increased the borrowing costs of Chinese enterprises [5]. However, most of this evidence remains reduced-form and provides limited insight into the firm-level transmission channels through which geopolitical shocks affect debt pricing.

2.2 Supply chains as the transmission channel

Supply chain disruption is a plausible mechanism. Trade frictions affect not only export demand and revenue but also input procurement, supplier reliability, inventory management, and the stability of customer–supplier relationships [6]. The global production network can transmit external shocks to cash flow volatility, working capital pressure and default risk [7]. Previous studies have shown that supply chain disruptions have persistent effects on valuation and risk [8], while newer studies show that the debt market directly prices supply chain risks [9]. These studies show that when local political shocks disrupt supply chain relationships, lenders may reassess firms' solvency and demand higher risk premiums.

2.3 Institutional context and heterogeneous effects

The financing effect of geopolitical shocks is also likely to vary across firms. Cross-country evidence suggests that the response depends on institutional environments and firm characteristics [3]. In China, ownership matters because state-owned enterprises often enjoy stronger policy support, implicit guarantees, and easier access to credit; accordingly, trade frictions appear to raise debt costs more for non-state-owned firms [5]. The effect should also be stronger when information asymmetry or financing frictions are greater [10]. Operational resilience provides another boundary condition: firms with more flexible supply chains can absorb shocks more effectively, whereas firms with weaker resilience are more exposed to cash-flow disruptions and creditor reassessment [12,13].

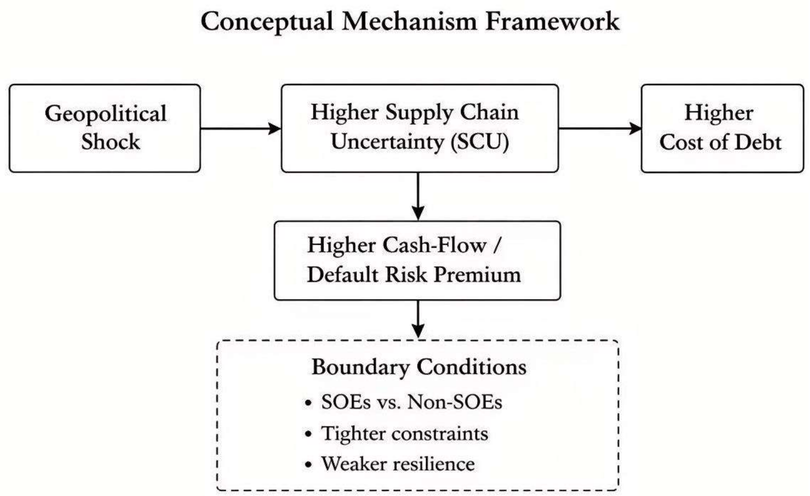
3. MECHANISM FRAMEWORK AND HYPOTHESES

3.1 Mechanism Framework

Geopolitical policy shocks can affect firms through higher input costs, reduced market access, and weaker supplier reliability [2,6]. When trade-policy uncertainty rises, firms often delay contracting, build precautionary buffers, and adjust procurement arrangements [2]. These responses are especially relevant in concentrated and multi-tier supply chains, where shocks can disrupt key supplier-customer relationships and make dependence on major trading partners less predictable. Such disruption raises supply chain uncertainty (SCU) [6,7]. Higher SCU can increase cash-flow volatility and working-capital pressure, weakening creditors' assessment of credit quality and increasing required risk premiums [8,9].

Figure 1 summarizes the mechanism. Geopolitical trade shocks may raise debt financing costs directly and indirectly through SCU, with transmission varying by ownership, financing constraints, and supply chain resilience. This motivates H2–H5.

Figure 1. Conceptual mechanism framework.



3.2 Hypotheses

In the hypotheses below, "geopolitical trade shock" refers to the policy shock generated by the 2018 escalation of U.S.–China trade frictions. The framework implies stronger debt-pricing effects among firms that are institutionally, financially, or operationally more vulnerable.

H1. (Main effect). Geopolitical risk exposure shocks increase corporate debt financing costs.

H2. (Mechanism). Supply chain uncertainty mediates the effect of geopolitical risk exposure shocks on the cost of debt.

H3. The effect is stronger for non-state-owned enterprises (SOEs vs. non-SOEs).

H4. The effect is stronger for firms with tighter financing constraints (measured using the SA index [11]).

H5. The effect is stronger for firms with weaker supply chain resilience.

4. DATA, VARIABLES, AND EMPIRICAL DESIGN

4.1 Sample and data

The sample covers Chinese A-share listed firms from 2010 to 2024. Firm-level financial, governance, and ownership data come from CSMAR. I exclude financial firms and ST firms and drop observations with missing values for key variables. All continuous variables are winsorized at the 1st and 99th percentiles. The final sample contains 41,675 firm-year observations.

4.2 Variable Construction

4.2.1 Dependent Variable: Cost of Debt

The cost of debt (COD) is measured as interest expense divided by average interest-bearing liabilities, where liabilities are averaged over the beginning and end of the year. As a robustness measure, COD2 scales interest and related financial expenses by total liabilities.

$$COD_{it}=\frac{InterestExpense_{it}}{AvgInterestBearingDebt_{it}} \tag{1}$$

$$COD2_{it}=\frac{InterestExp_{it}+FeeExp_{it}+OtherFinExp_{it}}{TotalLiab_{it}} \tag{2}$$

4.2.2 Key Explanatory Variable: Geopolitical Risk Exposure Shock

The 2018 escalation of U.S.–China trade frictions is treated as the exogenous policy shock. Postt equals one from 2018 onward. Ex ante exposure is measured as the firm's average overseas-revenue share over 2015–2017, which avoids post-treatment adjustment. The main regressor is Exposurei × Postt in a continuous-treatment DID design.

"$$Exposure_i=\frac{1}{|T_{pre}|}\sum_{t\in T_{pre}}\frac{OverseasRevenue_{it}}{TotalRevenue_{it}},\quad T_{pre}=\{2015,2016,2017\}. \tag{3}$$"

$$Shock_{it}=Exposure_i\times Post_t \tag{4}$$

4.2.3 Mediator: Supply Chain Uncertainty

Supply chain uncertainty (SCU) is measured as the three-year rolling standard deviation of supply chain concentration, where concentration is the average of top-five customer concentration and top-five supplier concentration. Higher SCU indicates less stable reliance on major trading partners.

"$$SC_{it}=\frac{Cust5_{it}+Supp5_{it}}{2} \tag{5}$$"

"$$SCU_{it}=\sigma(SC_{i,t-2},SC_{i,t-1},SC_{i,t}) \tag{6}$$"

4.2.4 Control Variables

Controls include policy support, firm size, profitability (ROA), leverage, asset turnover, sales growth, Tobin's Q, industry concentration (HHI), ownership concentration, board size, board independence, and female executive share. Table 1 defines all variables.

Table 1. Variable definitions.

Category	Variable	Definition
Outcome	COD	Interest expense / average interest-bearing liabilities
Robustness outcome	COD2	(Interest expense + fee expense + other financial expenses) / total liabilities
Main regressor	$Shock_{it}$	$Exposure_i \times Post_t$
Exposure component	$Exposure_i$	Average share of overseas operating revenue in total operating revenue over 2015–2017
Timing component	$Post_t$	1 for 2018 and later; 0 otherwise
Mediator	SCU_{it}	Three-year rolling standard deviation of supply chain concentration
Controls	X_{it}	Policy support, size, ROA, leverage, asset turnover, growth, Tobin's Q, HHI, Top 1, board size, board independence, female executive share

5. EMPIRICAL STRATEGY

The baseline specification is:

$$COD_{it}=\alpha+\beta_1 Shock_{it}+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it}. \tag{7}$$

where Exposurei is the firm's average overseas-revenue share over 2015–2017, Postt equals one for 2018 and later, and Xit is a vector of time-varying controls. Firm and year fixed effects absorb time-invariant heterogeneity and common shocks, and standard errors are clustered at the firm level. The coefficient on Shockit captures the incremental post-2018 change in debt costs for firms with higher pre-shock exposure.

To assess dynamic identification, I estimate an event-study specification:

$$COD_{it}=\sum_{k\neq -1}\beta_k\left(Exposure_i\times D_t^k\right)+\gamma' X_{it}+\mu_i+\lambda_t+\varepsilon_{it}, \tag{8}$$

where relative-year indicators are defined around the 2018 shock and 2017 is omitted as the reference year. Pre-shock interaction terms test parallel trends, while post-shock terms trace the timing and persistence of the treatment effect.

To test the mechanism, I follow Baron and Kenny and confirm the indirect effect with a Sobel test [14,15]. In addition to the baseline total-effect equation, I estimate the mediator and outcome equations below:

$$SCU_{it}=a_1 Shock_{it}+g' X_{it}+\mu_i+\lambda_t+\varepsilon_{it}, \tag{9}$$

and

$$COD_{it}=d_1 Shock_{it}+d_2 SCU_{it}+g' X_{it}+\mu_i+\lambda_t+\varepsilon_{it}. \tag{10}$$

Mediation is supported if Shock predicts SCU, if SCU is positively associated with COD conditional on Shock, and if the coefficient on Shock declines after SCU is included. The indirect effect equals a1 × d2. A significant Sobel statistic indicates that SCU contributes to the transmission from trade shocks to debt pricing.

6. EMPIRICAL RESULTS

6.1 Descriptive Statistics and pairwise correlations

Table 2 reports descriptive statistics. Mean COD is 0.054 (median 0.047), indicating substantial variation in borrowing costs. Mean pre-shock exposure is 0.065, with a median of zero and a maximum of 0.798, suggesting that many firms have little overseas revenue while a smaller group is highly exposed to external trade shocks. Mean SCU is 0.049, showing variation in the stability of major trading relationships.

Table 2. Descriptive statistics of the main variables.

Variable	N	Mean	SD	Min	Median	Max
COD	41,675	0.054	0.050	0.000	0.047	0.523
Pre-shock exposure	41,675	0.065	0.154	0.000	0.000	0.798
SCU	41,675	0.049	0.047	0.002	0.034	0.246
PS	41,675	0.004	0.005	0.000	0.003	0.027
Size	41,675	22.278	1.288	19.850	22.072	26.276
ROA	41,675	0.036	0.065	-0.219	0.036	0.219
Lev	41,675	0.422	0.204	0.050	0.414	0.896
ATO	41,675	0.631	0.430	0.076	0.537	2.622
Growth	41,675	0.137	0.350	-0.552	0.088	1.978
Tobin's Q	41,675	2.003	1.239	0.836	1.601	7.946
HHI	41,675	0.049	0.073	0.007	0.016	0.380
Top1	41,675	33.488	14.819	8.258	31.076	74.018
Board	41,675	8.407	1.618	5.000	9.000	14.000
Indep	41,675	0.378	0.054	0.333	0.364	0.571
Female	41,675	0.174	0.169	0.000	0.167	0.667

Note: The table is based on the full estimation sample of 41,675 firm-year observations.

Table 3 reports pairwise correlations. COD is positively correlated with pre-shock exposure (0.010, $p < 0.05$) and SCU (0.020, $p < 0.01$), while pre-shock exposure and SCU are negatively correlated (-0.090, $p < 0.01$). These magnitudes are small and only provide preliminary, non-causal evidence.

Table 3. Pairwise correlations among the core variables

Variable	COD	Pre-shock exposure	SCU
COD	1.000		
Pre-shock exposure	0.010**	1.000	
SCU	0.020***	-0.090***	1.000

Note: This table reports pairwise Pearson correlations for the full sample (N = 41,675). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

6.2 Baseline results and dynamic effects

Table 4 presents the baseline DID results. Shock is positive and significant at the 1% level in both specifications. With full controls, the coefficient of 0.014 implies that a 10-percentage-point increase in pre-shock exposure is associated with a 0.14-percentage-point increase in post-2018 debt costs, or about 4.95% of the sample mean. This supports H1.

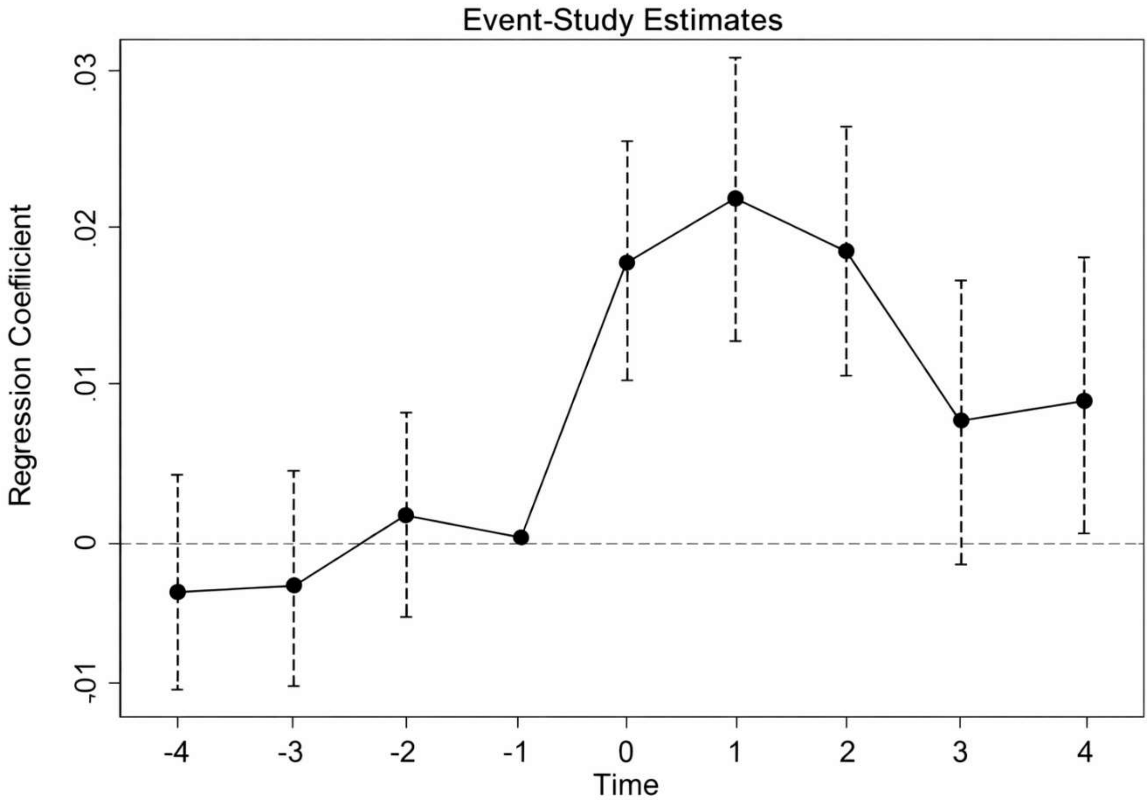
Table 4. Baseline DID estimates.

	(1)	(2)
Dependent variable	COD	COD
Shock	0.014*** (3.914)	0.014*** (3.823)
Controls	No	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	41,675	41,675
R^2	0.015	0.023

Note: Shock = Exposure × Post. t-statistics are in parentheses. Controls are omitted. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2 shows that the pre-shock coefficients are close to zero and statistically not significant, which supports the parallel-trends assumption. By contrast, the coefficients for 2018, 2019, and 2020 are positive, indicating that borrowing costs rose after the escalation of trade frictions. The effect weakens after 2020, consistent with partial adaptation through supply-chain and financing adjustments.

Figure 2. Event-study estimates and parallel-trends test.



Note: This figure plots the coefficients on the interaction between pre-shock exposure and relative-year indicators, with k = -1 omitted as the reference period. Vertical bars denote 95% confidence intervals.

6.3 Robustness Checks

Table 5 reports the robustness results. The positive effect of Shock remains under alternative specifications, including lagged treatment terms, COD2 as the outcome, Tobit estimation, exclusion of 2020–2022 observations, and 3%

winsorization. The two-period lag coefficient is small and statistically insignificant, suggesting that the increase in financing costs is concentrated around the shock period rather than persistent.

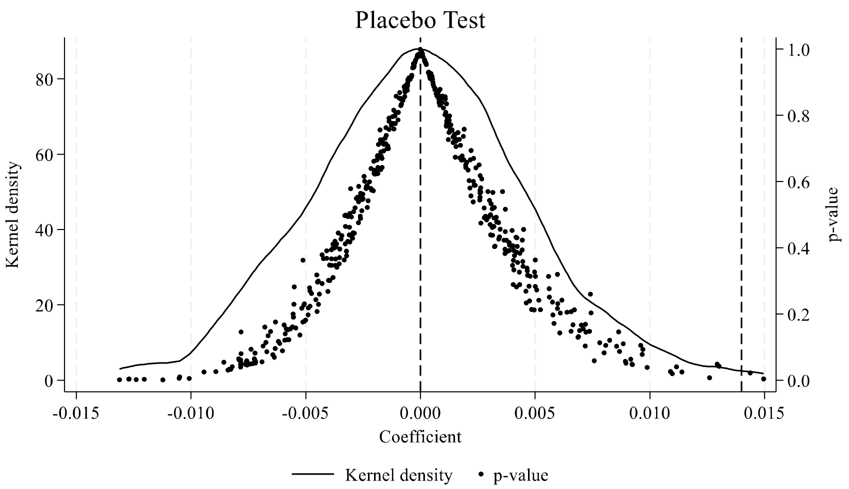
Table 5. Robustness checks.

	Lag 1	Lag 2	COD2	Tobit	Excl. 2020–2022	3% winsor
Dependent variable	COD	COD	COD2	COD	COD	COD
Estimator	FE OLS	FE OLS	FE OLS	Tobit	FE OLS	FE OLS
Shock	0.009** (2.572)	0.001 (0.207)	0.003*** (2.755)	0.007*** (3.418)	0.014*** (4.001)	0.008*** (2.674)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,421	30,733	41,675	41,675	30,532	41,675

Note: Each column reports the coefficient on Shock from an alternative specification; t-statistics are reported in parentheses. Control variables are omitted for brevity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This paper also conducts a placebo test based on 500 random reassignments of pre-shock exposure. Figure 3 shows that the placebo estimates are centered near zero, whereas the actual baseline estimate (0.014) lies in the far right tail. This pattern makes it unlikely that the main result is driven by random assignment.

Figure 3. Placebo test based on 500 random reassignment simulations.



Overall, the baseline result is robust to alternative timing assumptions, outcome measures, estimation methods, and sample restrictions.

6.4 Channels and Boundary Conditions

Table 6 reports the mediation results. The negative pairwise correlation between pre-shock exposure and SCU in Table 3 reflects unconditional cross-sectional differences in firms' baseline supply-chain structures. By contrast, the positive coefficient on Shock in Table 6 captures the post-2018 within-firm increase in SCU among more exposed firms relative to less exposed firms. The two patterns are therefore not contradictory. Shock has a positive total effect on COD (β = 0.014, t = 3.823) and also increases SCU (β = 0.009, t = 2.650). When SCU is added to the COD equation, SCU remains positive and significant (β = 0.016, t = 2.452), while Shock also remains positive and significant (β = 0.014, t = 3.782). The Sobel statistic is 2.406 (p = 0.016), and the proportion mediated is 0.010, indicating a statistically significant but economically modest mediation effect.

Table 6. Mediation analysis: the transmission role of supply chain uncertainty

	(1) Total effect	(2) Mediator equation	(3) Outcome equation
Dependent variable	COD	SCU	COD
Shock	0.014*** (3.823)	0.009*** (2.650)	0.014*** (3.782)
SCU			0.016** (2.452)
PS	0.012 (0.149)	-0.001 (-0.019)	0.012 (0.149)
Size	-0.004*** (-3.511)	0.001 (0.567)	-0.004*** (-3.522)
ROA	-0.040*** (-5.335)	-0.023*** (-3.499)	-0.039*** (-5.282)
Lev	0.019*** (4.451)	0.003 (0.659)	0.018*** (4.440)
ATO	0.006*** (3.277)	-0.005*** (-2.841)	0.006*** (3.325)
Growth	0.004*** (4.877)	0.014*** (14.096)	0.004*** (4.640)
TobinQ	0.000 (0.825)	0.000 (1.161)	0.000 (0.806)
HHI	-0.010 (-0.893)	0.043*** (4.107)	-0.011 (-0.957)
Top1	-0.000*** (-3.293)	-0.000 (-0.411)	-0.000*** (-3.291)
Board	0.001 (1.504)	-0.001** (-2.227)	0.001 (1.538)
Indep	-0.004 (-0.425)	-0.013 (-1.319)	-0.004 (-0.404)

Table 6. (continued) Mediation analysis: the transmission role of supply chain uncertainty

	(1) Total effect	(2) Mediator equation	(3) Outcome equation
Dependent variable	COD	SCU	COD
Female	0.002 (0.713)	0.000 (0.112)	0.002 (0.712)
_cons	0.112*** (5.229)	0.067*** (3.103)	0.111*** (5.183)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Sobel test (z)			2.406
p-value			0.016
Proportion mediated			0.010
Indirect/direct ratio			0.011
Observations	41,675	41,675	41,675
R^2	0.023	0.077	0.023

Note: Shock = Exposure × Post. Coefficients are reported with t-statistics in parentheses. Columns (1) and (3) use COD, while column (2) uses SCU. All specifications include the baseline controls, firm fixed effects, and year fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Figure 4 summarizes the mediation pattern: geopolitical exposure shocks increase SCU, and higher SCU is associated with higher debt costs, while the direct effect of Shock remains positive. The indirect effect is statistically significant but economically modest, so the evidence is more consistent with partial mediation than with full mediation.

Figure 4. Mediation mechanism: the transmission role of supply chain uncertainty.

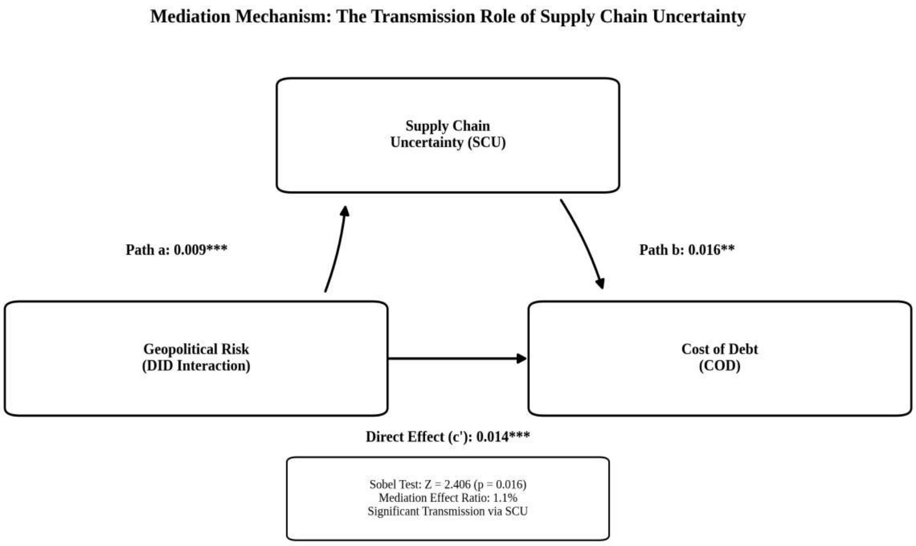


Table 7 reports heterogeneity results by ownership, financing constraints, and supply chain resilience. The coefficient on Shock is larger in the non-state-owned, high-financing-constraint, and low-resilience subsamples. These results are consistent with H3–H5 and suggest that the debt-pricing effect of geopolitical trade shocks is more pronounced in firms with weaker institutional support, tighter financing conditions, or lower operational resilience

Table 7. Heterogeneity analysis across ownership, financing constraints, and supply chain resilience.

Variable	(1) SOEs	(2) Non-SOEs	(3) High FC	(4) Low FC	(5) High resilience	(6) Low resilience
$Shock_{it}$	0.006 (0.986)	0.010** (2.384)	0.019*** (3.405)	0.011** (2.213)	0.008 (1.601)	0.019*** (3.349)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,124	27,551	20,833	20,842	20,178	21,497
R^2	0.023	0.030	0.019	0.033	0.021	0.024

Notes: This table reports subsample regressions by ownership, financing constraints, and supply chain resilience. All columns use the baseline controls and include firm and year fixed effects. t-statistics are reported in parentheses.

7. DISCUSSION AND IMPLICATIONS

This study contributes to the operations–finance literature by showing how geopolitical trade shocks affect debt pricing through firm-level operational instability. The larger effects observed in non-state-owned firms, financially constrained firms, and low-resilience firms further clarify the conditions under which this response is more pronounced.

These findings also have practical implications. For managers, supply chain resilience is both an operational issue and a financing issue. Diversifying suppliers and customers, improving supply chain visibility, strengthening emergency procurement arrangements and maintaining liquidity buffers may help limit the rise in financing costs under geopolitical shocks [12,13]. For policymakers, measures to reduce information frictions, keep credit channels open, and support supply chain resilience may help mitigate adverse debt-pricing responses during periods of geopolitical uncertainty [10,12,13].

8. CONCLUSION

This paper uses the 2017–2018 escalation of U.S.–China trade frictions as a quasi-natural experiment. The results show that Chinese listed firms with higher pre-shock overseas-sales exposure experienced larger increases in debt financing costs after 2018. The effect is concentrated in 2018–2020. The mediation effect through supply chain uncertainty is statistically significant but economically modest, and the effect is larger in non-state-owned firms, financially constrained firms, and firms with weaker supply chain resilience. Overall, the evidence suggests that geopolitical trade shocks can raise debt financing costs, with SCU serving as one statistically significant but economically modest transmission channel.

There are two limitations of this study. First of all, the degree of exposure to trade friction is measured using the intensity of overseas sales before the shock, rather than based on supply chain data at the transaction level, which limits the accuracy of transmission path observation. Secondly, the sample is limited to listed companies in China, so the external validity of the conclusion in other markets and company types needs to be carefully evaluated. Future research could use more detailed supplier–customer network data, bond- or loan-level pricing measures, and cross-country samples to examine how institutional environments shape the transmission of geopolitical shocks from operations to finance.

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