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Monitoring Firms, Weathering Shocks: The Effect of Analyst Coverage on Supply Chain Resilience

Jingshun Zhang
Beihang University, China

* Corresponding Author: **Jingshun Zhang**

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Abstract
Amid the wave of escalating global economic uncertainty, intensifying geopolitical tensions, and rising supply chain vulnerabilities, whether and how financial analysts as key capital market participants and information intermediary influence corporate supply chain resilience remains an important yet unsolved question. Using a large sample of Chinese firms, we find that firms with greater analyst coverage is associated with stronger supply chain resilience. To address endogeneity problems, we first use expected analyst coverage as an instrumental variable and obtain qualitatively similar results. We then exploit a quasi-natural experiment in which brokerage closures and mergers exogenously reduce analyst coverage, and we show that supply chain resilience weakens after these events. Analyses of the economic mechanisms indicate that the baseline effect is stronger for firms with higher information asymmetry or more severe financing constraints. Heterogeneity tests further reveal larger effects among state owned enterprises, among firms with lower supply chain efficiency, and among firms that operate across greater geographic distances. Overall, our study provides novel evidence and offers a deeper understanding of how sell-side analysts enhance the efficiency of supply chain network.

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Keywords: Financial Analyst, Analyst Coverage, Supply Chain Resilience, Information Asymmetry, Financing Constraints

1. Introduction

Global supply chains have increasingly been exposed to severe disruptions in recent years. Natural disasters and extreme weather events have posed persistent challenges, while the outbreak of COVID-19 in 2019 triggered unprecedented large-scale breakdowns across international supply networks (Celestin & Sujatha, 2024) [16] (Ivanov, 2024) [45]. These shocks revealed the inherent fragility of global supply chains and highlighted the lack of preparedness among many firms to cope with imminent threats (Choi et al., 2023) [21]. However, today's frequent disruptions in cross-border logistics have brought production and transportation activities to a standstill. Beyond short-term survival, firms must strategically adapt to an increasingly volatile, uncertain, complex, and ambiguous environment to achieve sustainable development (Ortiz-Avram et al., 2024) [73] (Atanassova et al., 2025) [5]. Against this backdrop, issues related to supply chains, blockchains, and industrial networks have attracted growing attention, leading to a notable expansion of scholarly research in these areas.

To prevent operational disruptions, firms must move beyond the traditional cost–efficiency orientation and adopt a multidimensional approach to addressing vulnerabilities to strengthen supply chain resilience (Pettit et al., 2010) [76] (Ivanov & Dolgui, 2021) [46]. Prior studies contend that "resilience" reflects a firm's capacity to recover quickly from disruptive events—either by restoring normal operations or achieving superior performance (Shuai et al., 2011) [90] (Mandal, 2012) [65]. Rather than merely managing risk, resilience entails responding to risks more effectively and cost-efficiently than competitors, thereby securing competitive advantages (Hamel & Valikangas, 2004) [39] (Yao & Meurier, 2012) [102]. Due to the occurrence of disruptive events on a global scale and their potential impacts on corporate competitiveness and continuity, firms should remain alert to unexpected shocks and respond with immediate mitigation measures. Although catastrophic events are largely unpredictable, their cascading effects can often be assessed through subtle, easily overlooked signals. Consequently, supply chain resilience (SCR) has garnered significant interest from researchers and practitioners in recent years. In the context of heightened macroeconomic shocks, scholarly interest in supply chain resilience and related fields has continued to grow.

Recently, scholarly inquiry has increasingly focused on the nexus between financial analysts and supply chain level dynamics. Luo and Nagarajan (2014) [62] examines the determinants and consequences of analysts becoming “supply-chain analysts”—i.e., simultaneously covering a supplier and its major customer. Evidence shows that information complementarities within the supply chain, between the supplier and its industry peers, and between the supplier’s key customer and other firms in the analyst’s portfolio all influence the decision to specialize along with the supply chain. Although supply-chain analysts produce more accurate forecasts for the supplier firms they follow, their forecast quality for the remaining firms in their coverage universe is lower. Guan et al. (2015) [35] find that analysts who cover a firm's major customer issue significantly more accurate earnings forecasts for the supplier than analysts who do not, indicating that supply-chain analysts benefit from informational complementarities along the chain and thereby improve their forecast accuracy. Son et al. (2016) [92] find that nearly three-fifths of these reports contain supply-chain information related to the company’s supply chain. At the report level, supply-chain-related content in analyst reports exhibits significant industry effects.

This study examines whether and how analyst coverage influences corporate supply chain resilience. The importance of this question lies in two aspects. First, existing literature on the economic consequences of analyst coverage largely centers on two streams: one in stock pricing, focusing on how analyst attention, forecast quality and stock recommendations influence investor decisions and price formation (Barber et al., 2006) [7] (Bradshaw et al., 2013) [12] (Li et al., 2025) [57]; the other in the domain of corporate governance, emphasizing analysts’ role as an external governance mechanism (Aguilera et al., 2015) [1] (Chen et al., 2015) [20] (Jain & Jamali, 2016) [47]. Research on the interaction between analysts and supply chains, however, remains scarce. Investigating the impact of analysts on supply chain resilience thus fills an important gap in the literature and provides empirical evidence and insights for understanding supply chain disruptions in the current global context. Second, given that the macroeconomic environment has been repeatedly challenged by shocks that threaten supply chains, global uncertainty has risen significantly. To ensure supply chain security and stability, this study offers decision- making implications for supply chain firms, extends the understanding of analysts’ influence in this domain, and provides empirical evidence to guide firms in responding to market and environmental changes shaped by analysts, thereby offering practical suggestions for addressing such events.

We employ a sample of Shanghai and Shenzhen A-share listed companies from 2005 to 2023. This study employs supply–demand volatility within the supply chain as a proxy for supply chain resilience, serving as the dependent variable. Drawing on the methodology of Shan et al. (2014) [87], it utilizes the volatility of supply and demand within the supply chain as a proxy for supply chain resilience and constructs a two-way fixed-effects model to empirically investigate the impact of analyst attention on supply chain resilience. The explanatory variable is the firm-level measure of analyst coverage, defined as the number of analysts following a given firm in each year. The empirical results show a significant positive relationship between analyst coverage and supply chain resilience. The baseline results may be biased due to omitted variables, reverse causality, or model misspecification. However, after controlling for a series of covariates and fixed effects, the results remain robust and significant.

To address endogeneity issues, we employ instrumental variables and qua-si nature experiments. We adopt the analyst expected coverage proposed by Yu (2008) [103] as the instrumental variable, which captures changes in brokerage size. According to Yu (2008) [103], brokerage size is primarily driven by fluctuations in its own revenue or profit and is unrelated to the firm characteristics of the companies covered by its analysts. The IV estimates indicate that analyst coverage has a significant positive effect on supply chain resilience. To further validate the findings, we employ brokerage closures and mergers as quasi-natural experiments that weaken analyst coverage. As shown in Kelly and Ljungqvist (2012) [50], brokerage closures represent an exogenous source of variation in analyst coverage, which should affect corporate supply chain resilience only through changes in analyst coverage. The results show that for firms experiencing brokerage closures and mergers, the positive effect of analyst coverage on supply chain resilience is attenuated, lending support to the main hypothesis of this study.

The mechanism tests yield the following findings: First, when firms operate under conditions of heightened information asymmetry, the costs associated with acquiring, processing, and interpreting relevant information increase substantially (Armstrong et al., 2011) [3] (He et al., 2013) [40]. These higher costs translate into elevated transaction frictions, making it more difficult for supply chain partners to coordinate effectively and sustain stable operations. Under such circumstances, financial analysts play a particularly critical informational role. By collecting, synthesizing, and disseminating firm- specific and industry-related information, analysts help mitigate information asymmetry within supply chains. This reduction in information gaps lowers transaction costs, facilitates more efficient coordination among firms, and ultimately enhances supply chain resilience. To empirically validate this mechanism, we use stock liquidity and the degree of earnings management to measure the level of information asymmetry. The results consistently show that when firms face higher levels of information asymmetry, the marginal effect of analyst coverage on supply chain resilience becomes significantly stronger.

Second, for firms that experience severe financing constraints, analysts’ attention plays a particularly important role in reducing these frictions (Singh, 2024) [91]. By issuing research reports and disseminating firm-specific insights into the market, analysts send credible signals regarding firms’ financial health and growth prospects. These signals help to alleviate financing constraints by strengthening investor confidence, improving firms’ reputation in capital markets, and increasing their likelihood of accessing external capital.

With enhanced cash flow availability, firms are better positioned to maintain stable operations, invest in supply chain improvements, and respond more effectively to external shocks. To empirically test this mechanism, we employ the SA_index and the KZ_index as measures of financing constraints. The findings indicate that when firms are subject to more severe financing constraints, the marginal impact of analyst coverage on supply chain resilience is substantially amplified.

Heterogeneity tests help identify the conditional relationships between analyst coverage and supply chain resilience, thereby providing a deeper understanding of the underlying causal mechanisms. We find that the positive effect of analyst coverage on supply chain resilience is more pronounced in state-owned enterprises, in firms with relatively low supply chain efficiency, and in those operating across greater geographic distances within their supply chains. The results enhance the robustness of the findings. A series of robustness tests confirm that the results remain valid after validating the findings using propensity score matching (PSM) and the Heckman two-stage method, altering fixed effects, substituting variable measures, applying alternative calculation methods, and excluding observations from the financial crisis period.

The contributions of this paper are as follows. First, it provides the first causal evidence on the impact of analyst coverage on supply chain resilience and reveals how analysts' behavior triggers market- and firm-level supply chain responses, thereby enriching the scope of the literature on the economic consequences of analyst coverage. In related work, Li et al. (2025) [57] proposes valuing financial data by quantifying changes in analyst-influenced numerical indicators, while Nicolò et al. (2024) [70] shows that voluntary disclosure of sustainable development goals can improve the corporate information environment and enhance analyst forecast quality. Moreover, Xu et al. (2025) [100] documents that better ESG performance increases the readability of analyst reports and strengthens market reactions, whereas Liu et al. (2025) [60] finds that climate policy uncertainty depresses analysts' earnings forecasts by deteriorating firms' fundamentals. By situating the role of analysts within the context of China's securities market and current macroeconomic environment, this study provides empirical evidence on how analyst coverage influences supply chain resilience and fills an important gap in the literature. Such mechanisms differ from prior studies that mainly focus on financial information channels, as this paper highlights supply chain channels.

Second, this study extends research on analysts' influence on supply chain resilience from internal supply chain indicators to the broader network level, offering a valuable complement to the existing supply chain literature. Recent findings highlight the significance of external factors in shaping supply chain resilience: Jia and Li (2024) [49] and Qi et al. (2024) [77] demonstrate that digitalization enhances supply chain resilience, particularly in state-owned enterprises, although the effect diminishes when government subsidies increase, a result further supported by Song et al. (2025) [95]. Zhang et al. (2024) [104] shows that excessive litigation risk impedes supply chain resilience, while Lin and Li (2025) [58] emphasizes that both supply chain resilience and ESG performance contribute to sustainable corporate growth. Zhang (2025) [105] provides evidence that establishing Comprehensive Pilot Zones for Cross-border E-commerce significantly improves supply chain resilience through greater redundancy, lower concentration, and higher-quality innovation. Similarly, Ruan et al. (2025) [83] demonstrates that green finance policies significantly strengthen corporate supply chain resilience. Against this background, the present study not only captures how firms and markets respond to analyst-driven and policy- driven dynamics but also offers practical implications. Specifically, it provides supply chain firms with decision- making references for strategic planning and operational choices, helping them navigate market fluctuations and environmental changes induced by analysts.

The structure of the paper is as follows: Section 2 outlines the theoretical background and develops the hypotheses; Section 3 presents the research design and descriptive statistics; Section 4 reports the empirical results, including the main effects, endogeneity tests, mechanism analysis, heterogeneity tests, and robustness checks; Section 5 concludes.

2. Theoretical background and hypothesis development

2.1. Theoretical background

In the capital market, financial analysts mainly play two fundamental roles: information intermediaries and external governance agents. As information intermediaries, analysts serve as vital bridges connecting firms with investors by collecting, processing, and disseminating firm-specific and industry-level information, thereby enhancing market transparency and efficiency. As external governance agents, analysts perform a monitoring function that constrains managerial opportunism and aligns corporate decisions with shareholder interests. Through these dual roles, analysts not only facilitate the efficient allocation of capital in financial markets but also exert a profound influence on firms' internal governance and operational behavior, extending even to areas such as supply chain management and resilience.

Financial analysts' information function can be understood through the lens of information intermediaries, emphasizing their dual roles in information discovery and interpretation (Green et al., 2014) [34] (Huang et al., 2018) [42]. In the process of information discovery, analysts extract valuable intelligence from vast amounts of heterogeneous and often unstructured data, including public disclosures, industry information, and feedback from suppliers or customers (Huang et al., 2014) [43]. Field research such as online visits, interviews, and verification enables analysts to obtain critical insights that are not readily available through public channels, thereby improving the accuracy of their forecasts (Keskek et al., 2014) [51]. In the subsequent stage of information interpretation, analysts transform and contextualize data so that decision makers can understand and apply it effectively. This process involves simplifying complex information, providing contextual understanding, and integrating both qualitative and quantitative inputs to form coherent judgments (De Franco et al., 2015) [25]. Through these complementary functions, analysts play a crucial role in reducing information asymmetry between firms and investors, as well as among firms within supply chains (Martens & Sextroh, 2021) [66]. Within supply chain contexts, their information functions help identify potential risks such as demand volatility or supplier disruptions, enhance transparency and coordination, and ultimately contribute to greater supply chain resilience. From the perspective of agency theory, the principal–agent relationship emerged alongside the development of productivity and large-scale production (Eisenhardt, 1989) [30] (Shapiro, 2005) [88]. Within this relationship, two key problems arise: on the one hand, the division of labor makes it difficult for principals to manage firms effectively relying solely on their own abilities; on the other hand, agents, due to more specialized education and training, have both the opportunity and capability to undertake corporate management (Sappington, 1991) [85] (Ross, 2014) [80]. However, differences in the objectives of principals and agents inevitably give rise to conflicts of interest. In the absence of effective institutional constraints, agents may act in ways that are detrimental to the interests of principals (Eisenhardt, 1989) [30] (Jensen & Meckling, 2019) [48]. Within the agency theory framework, analysts play a crucial role. By mitigating agency problems, enhancing corporate governance efficiency, and facilitating the effective functioning of capital markets, analysts exert significant influence on reducing information asymmetry and improving overall market transparency.

In addition to their role in capital markets, analysts also contribute to corporate governance by monitoring managerial behavior, curbing opportunistic practices, and aligning managers' incentives with those of shareholders (Chung & Jo, 1996) [22] (Dyck et al., 2010) [29]. Through their earnings forecasts, research reports, and continuous evaluations, analysts impose external pressure on management, which enhances accountability and helps reduce agency costs. This oversight mechanism promotes transparency in corporate decision- making and discourages value-destroying activities such as earnings manipulation and inefficient investment. Moreover, analysts influence managerial incentives by shaping market expectations and reputational outcomes, encouraging firms to adopt strategies that emphasize sustainable growth rather than short-term performance. In this governance capacity, analysts indirectly affect firms' operational behavior, including supply chain management, by fostering prudent risk management and long-term strategic alignment, ultimately strengthening supply chain resilience.

2.2. Hypothesis Development

2.2.1. The Main Effect of Analyst Coverage on Supply Chain Resilience

Financial analysts, drawing on their professional expertise, engage in comprehensive examinations of firms' financial conditions, strategic orientations, and competitive environments (Bradshaw, 2011) [11] (zu Knyphausen-Aufseß et al., 2011) [105] (Yahaya, 2021) [101]. By performing their information function, synthesizing and interpreting this complex data, they deliver rigorous yet accessible insights to investors. Prior studies show that analysts can exploit information complementarities along the supply chain to significantly improve forecasting accuracy and stock-recommendation returns, ensuring that suppliers' stock prices reflect fundamental value (Pandit et al., 2011) [75] (Luo & Nagarajan, 2014) [62]. Research has shown that highly transparent supply chains can reprioritize and reprice resources within hours after a disruption, avoiding panic ordering or erroneous production cuts and shortening recovery cycles (Tan et al., 2022) [97] (Coşkun & Erturgut, 2024) [24]. while Reynolds (2024) [79] shows that firms with advanced information-sharing mechanisms recover production on average 5.7 days faster than firms with lower-grade mechanisms, directly enhancing supply chain resilience. These studies suggest that analysts, as interpreters and transmitters of supply chain risk information, effectively perform the functions of information discovery and interpretation. When supply chains face disruption risks, analysts can accelerate firms' recovery processes and enhance overall supply chain resilience.

In addition to their informational role, analysts also function as external monitors, thereby enhancing corporate governance and improving operational efficiency (Byard et al., 2006) [15] (Yu, 2008) [103] (Chen et al., 2015) [20]. Li et al. (2023) [56] provide evidence that in-depth investigations into supply and demand relationships help detect accounting irregularities and identify potential fraud in advance. Building on this logic, analysts' research reports can function as an external governance mechanism within the supply chain network, constraining firms' financial misconduct and promoting greater transparency. By reducing the likelihood of fraudulent behavior, analysts indirectly strengthen firms' financial health, enabling them to better cope with and recover from supply chain disruptions.

Overall, these studies suggest that by processing and interpreting supply chain information, analysts help reduce information asymmetry and enhance supply chain resilience. At the same time, their role as external governance agents strengthens corporate governance, which improves supply chain resilience.

Under these arguments, we assume the central hypothesis of this study is articulated as follows:

H1: Analyst coverage is positively associated with supply chain resilience.

The Moderating Effect of Information Asymmetry

In the context of supply chain operations, fluctuations in macroeconomic conditions propagate through supply chain networks, increasing the risk of supply chain disruptions. Analysts who cover firms within the supply chain are better positioned to accurately interpret the information transmitted through these networks. Due to the "bullwhip effect," even minor fluctuations in downstream demand are amplified as they move upstream, resulting in overcapacity or resource waste and misalignment of supply and demand (Lee et al., 1997) [54] (Bray & Mendelson, 2012) [13] (Song & Zhang, 2025) [94]. Within supply chains, changes in consumer demand can be amplified through the bullwhip effect, leading to inventory accumulation and heightened disruption risks. Limited information disclosure or distorted financial reporting reduces market transparency, increases the cost of acquiring and processing information, and restricts stakeholders' ability to accurately assess a firm's true condition (Duarte et al., 2008) [28] (Lambert et al., 2012) [52]. Together, these conditions exacerbate uncertainty, impair resource allocation, and heighten vulnerability to external shocks.

Recent studies showed that information sharing reduces information asymmetry and weakens the bullwhip effect in supply chains. By improving transparency and coordination between upstream and downstream firms, it enables more accurate demand forecasting and production planning, thereby minimizing demand distortion and enhancing supply chain stability and resilience (Lee et al., 2000) [55] (Chen & Lee, 2009) [19]. Against this backdrop, analysts, as professional information intermediaries, play a particularly vital role in mitigating the adverse consequences of information asymmetry. By collecting, interpreting, and disseminating comprehensive and credible information, analysts enhance transparency and reduce uncertainty (Healy

& Palepu, 2001) [41] (She, 2022) [89] (Salehi et al., 2023) [84]. Their research reports and evaluations not only guide investors and shareholders toward more informed decisions but also reduce coordination frictions and curbing managerial opportunism (Yu, 2008) [103] (Chen et al., 2015) [20] (Coşkun & Erturgut, 2024) [24]. Consequently, the marginal effect of analyst coverage on supply chain resilience becomes even more pronounced when firms face high levels of information asymmetry, where transparency is low and uncertainty is high.

Under these arguments, we propose the following hypothesis:

H2: The positive effect of analyst coverage on supply chain resilience is more pronounced for firms with higher levels of information asymmetry.

The Moderating Effect of Financial Constraints

Analyst coverage also serves as an external governance and monitoring mechanism in capital markets. By following firms and issuing research reports, earnings forecasts, and stock recommendations, analysts convey valuable information about a firm's fundamentals and prospects. When analysts provide favorable assessments of a firm's financial health and operational efficiency, market participants regard it as an indicator of firm quality. As a result, the firm is more likely to gain the trust of investors, lenders, and supply chain partners. This enhanced credibility can lower the firm's external financing costs and mitigate financing constraints, promoting a more stable financial foundation for sustaining operations and long-term investments (Irvine, 2003) [44] (Chang et al., 2006) [18] (Hallman et al., 2023) [38].

When firms facing high levels of financial constraints, external financing is often costly or difficult to obtain due to limited collateral, opaque information, or weak investor confidence. In such cases, analysts' monitoring roles become even more valuable. Analyst coverage can act as an external certification mechanism, improving the firm's reputation and reducing perceived credit risk, thereby easing access to external capital markets. Adequate liquidity enables firms to better withstand market fluctuations and operational shocks while allocating resources toward supply chain optimization, innovation, and digital transformation (Reider & Heyler, 2003) [78] (Bao et al., 2012) [6] (Mohammadi, 2024) [68]. Consequently, the marginal effect of analyst coverage on supply chain resilience is stronger when firms are more financially constrained, as analyst influence effectively compensates for information opacity and financing frictions, enhancing firms' ability to build flexible and adaptive supply chain networks. Under these arguments, we propose the following hypothesis:

H3: The positive effect of analyst coverage on supply chain resilience is more pronounced for firms with more severe financing constraints.

3. Research design

3.1. Sample and data

We utilize data from the CSMAR database, covering the period from 2005 to 2023. To ensure data reliability. The selection of the sample from 2005 onwards is primarily based on considerations of data availability and quality. Prior to 2005, the documentation and analyst coverage of the Chinese securities market were relatively incomplete. We include firms that publish year-end financial reports. Firms in the financial sector and those subject to special treatment during the sample period are excluded, as their regulatory requirements, business practices, and capital structures differ from those of other industries. Additionally, all variables in the regression model are ensured to have no missing values. The final sample consists of 31,969 firm-year observations from 3,079 unique firms covering the period of 2005-2023.

3.2. Dependent variable

We adopt the bullwhip effect in supply chain relationships as a proxy for supply chain resilience (Shan et al., 2014) [87]. The bullwhip effect refers to the phenomenon where demand fluctuations amplify progressively along the supply chain, leading to greater inventory and production instability for upstream firms. Intuitively, the smaller the gap between production volatility and demand volatility, the better the supply chain can mitigate supply to demand mismatches through flexible adjustments in procurement, production, and inventory. We calculate this measure using a rolling five-year window, which not only reflects the degree of alignment at a specific point in time but also captures the dynamic adjustment process following shocks. Conceptually, this indicator reflects the supply chain's capacity to persist, adapt, and transform when facing disruptive events. For ease of interpretation and presentation, we take the inverse of the measure and divide it by 100, such that larger values indicate stronger supply chain resilience. The following model is used to measure the supply chain resilience:

$$SCR = -\frac{s(Production)}{sd(Demand)} /100 \qquad (1)$$

where $sd(\cdot)$ denotes the standard deviation calculated over a five-year window, including the current year and the preceding four years. *Demand* is measured by operating revenue, while *Production* is defined as *Demand* plus the change in net inventory.

2.1. Independent variable

The key independent variable is the firm-level measure of analyst coverage. Analyst coverage refers to the activities through which securities analysts monitor a specific firm, conduct investigations, interpret financial statements, and issue research reports (Bhushan, 1989) [9] (Brennan & Hughes, 1991) [14] (Yu, 2008) [103]. This process involves collecting and interpreting existing information, conducting field research, and continuously tracking the firm. Analysts integrate the information they collect into outputs such as earnings forecasts and research reports, which are then used to provide investment recommendations. Following the prior study, analyst coverage is defined as the number of distinct analysts who have signed reports on the firm within a given year. This variable is then transformed by taking its natural logarithm.

2.2. Model specification

To assess the effect of analyst coverage on supply chain resilience, we estimate the following Ordinary Least Squares (OLS) regression model:

$$SCR_{i,+1} = \beta_0 + \beta_1 \cdot Ln\_coverage_{i,t} + \beta_2 \cdot Controls_{i,t} + Industry\ FEs + Year\ FEs + \varepsilon_{i,+1} \qquad (2)$$

where i indices the firm, and t indices the year, and ε_{it+1} is the error term. $SCR_{i,+1}$ is the measure of supply chain resilience. $Ln\_coverage_{i,}$ is the measure of analyst coverage, which is measure at the end of the year. The industry fixed effects and year fixed effects account for unobserved shocks at the industry and temporal levels, respectively. Standard errors are clustered at the firm level to correct error autocorrelation.

This study aims to identify the causal effect of analyst coverage on supply chain resilience. To ensure that the observed relationship is truly driven by analyst coverage

Table 1: Descriptive statistics

(N=31,969)	Mean	Std.Dev.	P25	Median	P75
SCR	-0.1990	0.4578	-0.1506	-0.0503	-0.0194
Ln_coverage	1.3678	1.1825	0.0000	1.3863	2.3979
Ln_assets	22.2968	1.3148	21.3724	22.1199	23.0404
Ln_age	2.8203	0.3948	2.5649	2.8904	3.0910
Leverage	0.4596	0.1962	0.3091	0.4627	0.6085
ROA	0.0433	0.0609	0.0132	0.0383	0.0724
Return	0.2029	0.6763	-0.2260	0.0179	0.4098
Tobin_Q	1.9091	1.1987	1.1735	1.5125	2.1635
CFO	0.0499	0.0712	0.0099	0.0483	0.0910
EBIT_volatility	0.0316	0.0322	0.0116	0.0211	0.0392
Z_score	4.1855	4.6765	1.6671	2.7537	4.6963
Ln_board	2.2670	0.1784	2.1972	2.3026	2.3026
Independence	0.3708	0.0523	0.3333	0.3333	0.4000
Dual	0.2244	0.4172	0.0000	0.0000	0.0000
Top1	0.3547	0.1517	0.2348	0.3334	0.4607
Inst	0.4855	0.2314	0.3251	0.5086	0.6618
Big4	0.0685	0.2526	0.0000	0.0000	0.0000

Note: This table reports the descriptive statistics of the main variables used to estimate the baseline regression (i.e., Columns (2) of Table 2). Variable definitions are provided in Appendix A.

rather than confounding firm-specific characteristics, we include a comprehensive set of firm-level control variables in the model, including firm size (*Ln_assets*), firm age (*Ln_age*), leverage (*Leverage*), return on assets (*ROA*), annual stock return (*Return*), Tobin's Q (*Tobin_Q*), operating cash flow (*CFO*), earnings before interest and taxes (*EBIT_volatility*), Z-score (*Z_score*), board size (*Ln_board*), independent director ratio (*Independence*), dual leadership (*Dual*), top shareholder ownership ratio (*Top1*), institutional ownership (*Inst*), and whether the auditor is from one of the Big Four accounting firms (*Big4*). Detailed variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th levels to mitigate the potential impacts of outliers.

2.3. Descriptive statistics

Table 1 presents the descriptive statistics for key variables to illustrate the overall distribution of the data. The data spans from 2005 to 2023, and the descriptive statistics include the sample size, mean, standard deviation, maximum and minimum values, and median for each variable. The mean of supply chain resilience (SCR) is -0.1990, with a standard deviation of 0.4578, respectively, consistent with the findings of Shan et al. (2014) [87]. The meaning of analyst coverage (Ln_coverage) is 1.3678, with a standard deviation of 1.1825. This suggests that analyst coverage of firms in the sample exhibits substantial variability.

4. Empirical result

4.1. Baseline estimation results

Table 2 presents the baseline regression results examining the impact of analyst coverage (Ln_coverage) on supply chain resilience (SCR). Column (1) reports the regression results without any control variables. The coefficient of Ln_coverage is positive and highly significant, indicating that greater analyst coverage is associated with stronger supply chain resilience. Column (2) incorporates a set of control variables. The coefficient of Ln_coverage remains positive and statistically significant, suggesting that analyst coverage continues to have a robust effect after accounting for firm-specific characteristics. Column (3) further introduces industry and year fixed effects to control unobserved heterogeneity at the industry and temporal levels. Despite these additional controls, the coefficient of Ln_coverage remains positive and significant, reinforcing the conclusion that analyst coverage positively contributes to supply chain resilience.

[1] H1 is supported.

4.2. Endogeneity tests

Although the baseline results indicate that firms with greater analyst coverage exhibit stronger supply chain resilience, we remain concerned that this finding may be affected by endogeneity issues such as omitted variables, reverse causality, or misspecification of the regression model. To address these concerns, we conduct a series of additional tests designed to mitigate potential endogeneity biases.

4.2.1. Instrumental variable

In this study, we adopt the expected coverage rate as the instrumental variable, which reflects changes in brokerage firm size Yu (2008) [103]. According to the research, the size of a brokerage firm is primarily determined by its own

[1] To assess the economic significance of our estimates, we re-estimate the model using the raw number of analyst coverages (i.e., without the "logarithm of one plus" transformation) as the independent variable. Untabulated results show that the coefficient on this raw measure is 0.0038 and is significant at the 1% level. In terms of economic magnitude, a one-standard-deviation increase in the number of analyst coverages (10.0401, untabulated) corresponds to an absolute increase of 0.0386 (10.0401 × 0.0038) in supply-chain resilience, equivalent to 19.41% of its sample mean (0.1990) and 8.43% of its sample standard deviation (0.4578).

revenue or profit fluctuations and is unrelated to firm specific characteristics of the companies it covers. Therefore, changes in analyst coverage driven by variations in brokerage firm size constitute a reasonable source of exogenous variation, allowing us to better establish the causal direction of the relationship. The equations below are used to calculate expected coverage:

Table 2: Analyst coverage and supply chain resilience

	(1)	(2)	(3)
	SCR	***SCR***	***SCR***
Ln_coverage	0.0239***	0.0517***	0.0340***
	(11.274)	(19.547)	(7.221)
Ln_assets		-0.0583***	-0.0393***
		(-21.001)	(-5.222)
Ln_age		0.0056	-0.0017
		(0.815)	(-0.095)
Leverage		-0.2849***	-0.0598
		(-17.605)	(-1.402)
ROA		-0.1171***	0.1157
		(-2.702)	(1.583)
Return		-0.0041	0.0013
		(-1.170)	(0.274)
Tobin_Q		-0.0017	-0.0081
		(-0.989)	(-1.317)
CFO		0.4643***	0.2334***
		(13.118)	(4.616)
EBIT_volatility		0.2147***	0.1934*
		(3.444)	(1.895)
Z_score		-0.0024***	-0.0029*
		(-6.737)	(-1.681)
Ln_board		-0.0011	0.0302
		(-0.065)	(0.766)
Independence		-0.2275***	-0.0797
		(-4.364)	(-0.713)
Dual		0.0342***	0.0083
		(5.563)	(1.126)
Top1		-0.1126***	-0.0371
		(-5.698)	(-0.963)
Inst		-0.0286**	-0.0040
		(-2.052)	(-0.155)
Big4		0.0235**	0.0224
		(2.214)	(0.773)
Observations	33,397	31,969	31,968
R-squared	0.004	0.070	0.212
Controls	No	Yes	Yes
Industry fixed effects	No	No	Yes
Year fixed effects	No	No	Yes
SE clustered by	Firm	Firm	Firm

$$ExpCoverage_{i,t} = \sum_{j=1}^{n}\left(\frac{Brokersize_{j,t}}{Brokersize_{j,0}}\right) \times Coverage_{i,j,0} \quad (3)$$

where $Brokersize_{j,0}$ and $Brokersize_{j,t}$ are the number of analysts employed by broker j in the benchmark year zero and year t, respectively. $Coverage_{i,j,0}$ is the size of the coverage for firm i from broker j in year zero. $ExpCoverage_{i,t}$ is the total expected coverage of firm i from all brokers in year t. We adopt 2005 as the benchmark year for expected analyst coverage and require firms to be covered by at least one analyst in the benchmark year.

Column (1) of Table 3 represented the first-stage regression results, the coefficient of *ExpCoverage* is significant at 1% level, which means the relevance condition is satisfied. Column (2) reports the second-stage regressions of the supply chain resilience on analyst coverage, with expected analyst coverage (*ExpCoverage*) as the instrumental variable. The coefficient of instrumented *Ln_coverage* is significant, which supports the expectations.

4.2.2. Quasi-natural experiment

To further address potential endogeneity concerns, this study employs a quasi-natural experiment based on brokerage closures and brokerage mergers. This approach captures plausibly exogenous variations in analyst coverage (Kelly & Ljungqvist, 2012) [50]. The underlying logic is that brokerage firms often close their research departments in response to adverse changes in their own revenue streams from trading, market-making, or investment banking. These closures are primarily driven by internal strategic decisions rather than by the characteristics of the firms being covered by analysts. As such, brokerage closures serve as exogenous shocks that can be used to examine the causal effect of analyst coverage on firm outcomes.

To identify the impact of brokerage closures on firms at different points in time, this study employs a multi-period difference-in-differences (DiD) model and specifies the following empirical framework to assess the effect of brokerage closures on corporate supply chain resilience:

Table 3: Instrumental variable approach

	(1)	(2)
	Ln_coverage	***SCR***
ExpCoverage	0.0123***	
	(48.2559)	
Ln_coverage (instrumented)		0.0659***
		(5.4554)
Observations	16,563	16,563
R-squared	0.6046	0.0150
Control variables	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
SE clustered by	Firm	Firm

Note: This table reports the 2SLS regression results. Variables are defined in Appendix A. Robust t-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

$$\begin{aligned} SCR_{i,t+1} = \; & \beta_0 + \beta_1 \cdot Treatment_{i,t} \times Post_{i,t} \\ & + \beta_2 \cdot Treatment_{i,t} + \beta_3 \cdot Post_{i,t} \\ & + \gamma \cdot Controls_{i,t} + Industry\ FEs \\ & + Year\ FEs + \varepsilon_{i,t+1} \end{aligned} \tag{4}$$

where $Treatment_{i,t}$ is a binary variable that equals one if a firm is affected by brokerage closures or mergers, and zero otherwise. $Post_{i,t}$ is also a binary variable, which equals one if the period falls after the brokerage closure or merger event for the firm, and zero otherwise? To mitigate potential estimation bias and efficiency loss caused by highly unbalanced samples, and to better estimate causal effects, for all firms affected by brokerage closure or merger events, we adopt 1:1 nearest-neighbor propensity score matching using a logit model, with covariates consistent with the baseline regression. We retain only control firms that are most comparable to the treated firms in observable characteristics, then estimate the DiD model on the matched subsample to ensure that the results are primarily driven by brokerage closures and mergers.

The critical assumption in DiD model is that the time trends of treatment and control groups are the same. To satisfy the identification assumptions of the DiD framework, we construct a set of indicator variables for parallel trend testing. Specifically, the year of the brokerage closure is defined as the current year, while the pre-treatment and post-treatment periods are categorized accordingly. The pre-treatment period is grouped into three years prior to the event (*Pre-3*), which is omitted as the benchmark period, and the post-treatment period is captured using the *Post* indicator variable.

The results are reported in Table 4. Panel A shows the results of DiD regression. The coefficient on $Treatment_{i,t} \times Post_{i,t}$ is significantly negative at the 5% level, indicating that firms affected by brokerage closures experience a decrease in the number of covering analysts. Panel B reports the balancing *t*-tests for the covariates used in the matching process. All covariates pass the balance test. A total of 296 treated firms were successfully matched, resulting in a final sample of 592 firms and 7,658 firm-year observations. Panel C provides reliable evidence for the key assumption of DiD. Prior to the policy implementation, the estimated coefficients are statistically insignificant, indicating no significant difference between the treatment and control groups, which supports the parallel trend assumption and thereby enhances the credibility and robustness of our research findings. This result is consistent with our expectations.

4.3. The economic mechanisms

In the following section, the preceding analysis indicates that the positive effect of firms' analyst coverage with its supply chain resilience. Through this, the objective of this section is to examine whether the information channel and the financing constraint channel are the mechanism through which firms' analyst coverage increases supply chain resilience.

4.3.1. Information asymmetry mechanism

To evaluate the information channel, we use two proxies for information asymmetry. First, stock liquidity is employed as a proxy for information asymmetry (Goyenko et al., 2009) [33]. We use the turnover ratio (Turnover) to measure stock liquidity. Research has shown that analysts devote considerable attention to firms' supply chain characteristics and that supply chain-related content in analyst reports is positively associated with stock recommendation decisions, highlighting its informational value (Pandit et al., 2011) [75] (Son et al., 2016) [92]. In this context, analyst coverage is particularly consequential when stock liquidity is low. By functioning as professional information intermediaries, analysts gain access to more precise and comprehensive information about firms, which subsequently communicate to the market. This transmission of information narrows the gap between managers and investors, reduces transaction uncertainty, and mitigates supply chain risks by stabilizing expectations across stakeholders (Roulstone, 2003) [81] (Gao et al., 2020) [31]. Thus, analyzing stock liquidity provides a meaningful avenue to test whether the effect of analyst coverage on supply chain resilience operates through the channel of information asymmetry. In environments with higher information asymmetry, analysts are expected to have a greater marginal impact. Therefore, we expect the interaction term between analyst coverage and stock illiquidity to be significantly negative, suggesting that the effect of analyst attention on supply chain resilience is stronger when liquidity is low.

Table 4: Quasi-natural experiment: Brokerage closures and mergers

Panel A PSM-DiD regression

	(1)
	SCR
Treatment × *Post*	-0.0609**
	(-2.0006)
Treatment	0.0894***
	(3.3027)
Post	0.0447
	(1.5722)
Observations	7,661
R-squared	0.2811
Control variables	Yes
Industry fixed effects	Yes
Year fixed effects	Yes
SE clustered by	Firm

Panel B Balancing *t*-test of the propensity score matching for DiD regression

Varname	Obs(0)	Mean(0)	Obs(1)	Mean(1)	Mean-diff	P-value
Ln_assets	296	22.120	296	22.287	-0.167	0.105
Ln_age	296	2.591	296	2.588	0.003	0.927
Leverage	296	0.437	296	0.449	-0.012	0.463
ROA	296	0.062	296	0.054	0.008	0.117
Return	296	0.267	296	0.197	0.070	0.127
Tobin_Q	296	2.098	296	1.985	0.114	0.316
CFO	296	0.051	296	0.052	-0.001	0.826
EBIT_volatility	296	0.028	296	0.029	-0.002	0.481
Z_score	296	4.746	296	4.678	0.067	0.875
Ln_board	296	2.294	296	2.303	-0.009	0.535
Independence	296	0.367	296	0.369	-0.002	0.618
Dual	296	0.250	296	0.255	-0.005	0.887
Top1	296	0.370	296	0.376	-0.006	0.635
Inst	296	0.521	296	0.533	-0.011	0.575
Big4	296	0.081	296	0.095	-0.014	0.545

Panel C Parallel trend test

	(1)
	SCR
Treatment × *Pre_3*	0.0183
	(0.5427)
Treatment × *Pre_2*	-0.0316
	(-0.8306)
Treatment × *Pre_1*	-0.0240
	(-0.6781)
Treatment × *Post*	-0.0671**
	(-2.1638)
Treatment	0.0955***
	(3.5691)
Pre_3	-0.0043
	(-0.1576)
Pre_2	0.0096
	(0.3842)
Pre_1	0.0014
	(0.0526)
Post	0.0452
	(1.5783)
Observations	7,661
R-squared	0.2812
Control variables	Yes
Industry fixed effects	Yes
Year fixed effects	Yes
SE clustered by	Firm

Note: This table reports the DiD regression results. Variables are defined in Appendix A. Robust *t*-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Second, we use earnings management as another proxy for information asymmetry. According to agency theory, conflicts of interest and information asymmetry exist between managers and shareholders (Eisenhardt, 1989) [30] (Jensen & Meckling, 2019) [48]. Managers may manipulate financial reports, creating information gaps that hinder investors and supply chain partners from accurately assessing a firm's true financial position (Lyon et al., 1999) [64] (Orshi et al., 2023) [72]. Higher levels of earnings management thus indicate deeper information asymmetry (Le & Trinh, 2022) [53]. By distorting financial reports, management obscures firm value, erodes investor trust, and invites persistent skepticism toward future disclosures.

We consider both real earnings management (REM) and accrual-based earnings management (AEM) (Roychowdhury, 2006) [82] (Cohen & Zarowin, 2010) [23]. We expect the interaction term to be significantly positive, indicating that the marginal effect of analyst coverage on supply chain resilience is more pronounced in firms with higher earnings management, consistent with the information asymmetry mechanism.

The results are represented in Panel A of Table 5. As shown in columns, the interaction term between Ln_coverage and Turnover is negative and significant at 5% level, which is consistent with the expectation. The interaction term between Ln_coverage and the proxy variables of earnings management is positive and significant. We interpret these results as indicating that higher information asymmetry strengthens the marginal value of analyst coverage for supply chain resilience. Moreover, the coefficient of Ln_coverageREM are more significant than Ln_coverageAEM, which means the firm's earnings management practices are more covert. H2 is supported.

Table 5: Analyst coverage and supply chain resilience – The economic mechanisms

Panel A Information asymmetry mechanism

	(1)	**(2)**	**(3)**
	SCR	***SCR***	***SCR***
Ln_coverage × Turnover	-0.0058**		
	(-2.0226)		
Turnover	0.0030		
	(0.6924)		
Ln_coverage × REM		0.0560***	
		(3.0835)	
REM		-0.2032***	
		(-4.9639)	
Ln_coverage × AEM			0.0738*
			(1.7472)
AEM			-0.3144***
			(-4.2931)
Ln_coverage	0.0429***	0.0241***	0.0301***
	(6.0166)	(4.1994)	(5.6711)
Observations	31,968	28,382	31,640
R-squared	0.2123	0.2209	0.2134
Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
SE clustered by	Firm	Firm	Firm

Panel B Financial constraints mechanism

	(1)	**(2)**
	SCR	***SCR***
Ln_coverage × SA_index	0.0460***	
	(3.3672)	
SA_index	-0.1195**	
	(-2.1297)	
Ln_coverage × KZ_index		0.0029**
		(2.4450)
KZ_index		-0.0164***
		(-4.6569)
Ln_coverage	0.2103***	0.0286***
	(3.9280)	(6.3629)
Observations	31,968	31,968
R-squared	0.2135	0.2132
Control variables	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
SE clustered by	Firm	Firm

Note: This table reports the OLS regression results. Variables are defined in Appendix A. Robust *t*-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.3.2. Financing constraint mechanism

Analysts' research activities provide signals that draw market attention, enhance investor confidence, and lower firms' financing costs. By easing financing constraints and improving access to external capital, analysts help firms secure stable cash flows to sustain operations and invest in supply chain improvements. This support enables firms to better withstand market fluctuations and external shocks, thereby strengthening supply chain resilience.

To capture financing constraints, we adopt two widely used indices: the *SA_index* and the *KZ_index*. We expected the interaction term between analyst coverage and the proxy of financing constraints to be significantly positive, which means the greater the financing constraints, the stronger influences of analysts. The results are reported in Column (4)-(5) of Table 5. Consistent with the expectation, the effect of the interaction term between *Ln_coverage* and *SA_index / KZ_index* is positive and significant at 1% / 5% level, which lends strong support to H3. We interpret these results as indicating that greater financial constraints enhance the marginal value of analyst coverage for supply chain resilience.

4.4. Heterogeneity tests

The preceding analysis confirmed the impact of analyst coverage on supply chain resilience and based on the results of the moderating effect regression model, demonstrated that analysts play a stronger role under conditions of severe information asymmetry and high financing constraints. Building on this, the study conducts a heterogeneity analysis by partitioning the sample into subsamples according to selected variables, to explore the sources and characteristics of this effect.

4.4.1. Firm ownership

In China's unique institutional environment, state-owned enterprises (SOEs), due to their distinct operational objectives and executive appointment mechanisms, often exhibit a higher degree of information asymmetry (Ding et al., 2020) [27] (Alduais et al., 2022) [2]. These firms not only pursue financial performance but also bear responsibilities such as promoting social equity and ensuring employment stability, which adds complexity to their operations. Executive appointments in SOEs are typically made by the government rather than through market-based competition, which may hinder information flow and reduce transparency, as executives are often more inclined to report to government authorities than to disclose information publicly.

Moreover, SOEs may have more complex internal governance structures and decision-making processes, further exacerbating information asymmetry (Ding et al., 2022) [26]. Given that executive incentives and accountability mechanisms in SOEs differ from those in non-SOEs, SOE executives may be less motivated to reduce information asymmetry, whereas their non-SOE counterparts face stronger pressures from market competition and performance-linked compensation. These ownership-based differences create unique patterns in information disclosure, managerial behavior, and risk management, which in turn affect corporate strategies and performance outcomes. Consequently, the level of information asymmetry in SOEs is likely to be higher, representing an important consideration for investors, regulators, and market participants. Panel A of Table 6 reports the baseline model regressions by splitting the sample into SOE and non-SOE subsamples. The difference in coefficients indicates that analysts play a stronger role in state-owned enterprises, which is consistent with the preceding theoretical rationale and hypotheses, and aligns with our expectations. The coefficient difference across these two subsamples is significant at the 10% level, providing robustness for the heterogeneity analysis.

4.4.2. Supply chain efficiency

Efficiency differences in supply chain operations are critical for optimizing management and strengthening competitiveness. Supply chain efficiency can be assessed across several dimensions, such as order fulfillment time, inventory turnover, transportation costs, quality control, and responsiveness. These dimensions capture how effectively resources are allocated and coordinated across the supply chain (Gunasekaran et al., 2004) [37] (Coşkun & Erturgut, 2024) [24]. Factors influencing efficiency must be identified through systematic data collection and statistical analysis, which allow researchers to detect variations and uncover their underlying causes.

Drawing on prior studies, this paper adopts the working capital turnover ratio as a proxy for supply chain efficiency, a measure that has gained wide recognition in literature (Gaur et al., 2005) [32] (Lorentz et al., 2012) [61] (Song & Sun, 2017) [93]. Variations in supply chain efficiency reflect differences across multiple key performance indicators, which in turn have significant implications for firms' operating performance, customer satisfaction, and market competitiveness. Enhancing supply chain efficiency is therefore a central objective of firms' ongoing efforts toward improvement and management optimization. Panel B of Table 6 reports the baseline model regressions by splitting the sample into high-efficiency and low-efficiency subsamples based on the median level of supply chain efficiency. Consistent with expectations, the results show that the impact of analyst coverage on supply chain resilience is stronger in firms with low supply chain efficiency. The coefficient difference across these two subsamples is significant at the 1% level, further validating the robustness of the heterogeneity analysis.

4.4.3. Supply chain geographic distance

Considering the spatial distribution of upstream and downstream partners, differences in geographic distance can significantly affect supply chain operations and performance across several dimensions, including logistics costs, delivery time, market accessibility, and overall transportation expenses (Lorentz et al., 2012) [61] (Wiengarten & Ambrose, 2017) [98]. For instance, supply chains with geographically proximate partners often benefit from lower transportation costs and faster circulation of goods, thereby improving coordination and efficiency. In contrast, supply chains spanning longer distances are more likely to incur higher logistics costs, face longer lead times and encounter greater challenges in synchronizing operations.

Geographic distance also shapes the flexibility and responsiveness of supply chains. The greater the distance between various stages of the supply chain, the more difficult it becomes to transmit information and coordinate activities effectively, which may slow the response to market changes (Guangling et al., 2022) [36]. Under conditions of demand fluctuations or supply chain disruptions, longer distances can further amplify supply chain vulnerabilities and weaken resilience. Panel C of Table 6 reports the baseline model regressions by dividing the sample into high-distance and low-distance subsamples based on the median level of supply chain geographic distance. The results indicate that analyst coverage exerts a stronger impact on supply chain resilience among firms whose upstream and downstream partners are geographically distant. The cross-group difference is significant at the 10% level, implying a statistically meaningful difference between the two subsamples.

4.5. Robustness tests

To further ensure the robustness of our findings, we conducted a series of robustness checks. First, we employed propensity score matching (PSM) and the Heckman two-step procedure to address potential sample selection and self-selection biases. Second, we adopted alternative measures of supply chain resilience, defined as the negative value of the gap between production and demand volatility calculated over three-year and seven-year rolling windows (*SCR_3* or *SCR_7*). In addition, we constructed alternative indicators for analyst attention and supply chain resilience, including the number of analyst reports (*Ln_report*), supply chain concentration (*SCC*), and whether a firm's top five customers were replaced during the sample period (*CR*). The definitions of all variables are provided in Appendix A. Furthermore, we introduced additional fixed effects: province and city fixed effects, to account for regional heterogeneity, and we excluded potentially influential observations by removing firm-year data corresponding to the 2008–2009 global financial crisis and the 2019–2020 COVID-19 pandemic. The regression results, reported in Table 7, remain consistent and statistically significant across all robustness specifications, further reinforcing the validity of our conclusions.

5. Conclusion

Table 7: Analyst coverage and supply chain resilience﹣Robustness tests

Panel A PSM and Heckman two-step procedure

	(1)	(2)
	SCR	***SCR***
Ln_coverage	0.0278***	0.0344***
	(0.0055)	(0.0047)
Observations	14,274	31,968
R-squared	0.2274	0.2134
Control variables	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
PSM sample	Yes	No
Inverse Mills Ratio	No	Yes
SE clustered by	Firm	Firm

Panel B Alternative measures of analyst coverage and supply chain resilience

	(1)	(2)	(3)	(4)	(5)
	SCR_3	***SCR_7***	***SCR***	***SCC***	***CR***
Ln_coverage	-0.0505***	-0.0307***		0.0082***	0.0088***
	(-6.845)	(-7.504)		(4.194)	(2.999)
Ln_report			0.0282***		
			(7.321)		
Observations	28,939	25,494	31,968	23,599	5,913
R-squared	0.160	0.248	0.212	0.272	0.123
Control variables	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
SE clustered by	Firm	Firm	Firm	Firm	Firm

Panel C Alternative model specifications

	(1)	(2)	(3)
	Including Province fixed effects	**Including City fixed effects**	**Exclude time period during 2008-2009 and 2019-2020.**
	SCR	*SCR*	*SCR*
Ln_coverage	0.0299***	0.02996***	0.03446***
	(6.504)	(6.365)	(7.325)
Observations	31,968	31,960	24,756
R-squared	0.223	0.257	0.209
Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
SE clustered by	Firm	Firm	Firm

Note: This table reports the OLS regression results. Variables are defined in Appendix A. Robust *t*-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

This study examines the impact of analyst attention on firms' supply chain resilience in the Chinese context, where frequent macroeconomic shocks and policy-driven dynamics make resilience a crucial component of corporate survival and growth. The baseline regression results show a significant positive relationship between analyst coverage and supply chain resilience, suggesting that analysts play an important role beyond capital market outcomes by influencing firms' ability to adapt and respond to supply chain disruptions. To address potential endogeneity concerns, we adopt analysts' expected coverage as instrumental variables and further employ brokerage closures and mergers as exogenous shocks in a quasi-natural experiment setting. The consistency of the results across these identification strategies confirms the robustness of the findings. In addition, further analysis indicates that the positive effect of analyst coverage is more pronounced in firms characterized by higher levels of information asymmetry, proxied by earnings management and stock liquidity, and in firms subject to greater financial constraints, proxied by the *SA_index* and *KZ_index*. Heterogeneity analysis further reveals that the effect of analyst coverage on supply chain resilience is stronger for state-owned enterprises (SOEs), firms with relatively low supply chain efficiency, and firms operating across wider geographical distances within their supply chain networks. After a battery of robustness checks, including propensity score matching (PSM), Heckman two-stage procedure, alternative variable measurements, additional fixed effects, and the exclusion of potentially influential subsamples, the results remain robust.

From a theoretical perspective, this study extends the literature on the economic consequences of analyst coverage by shifting attention from traditional domains such as stock pricing, market efficiency, or corporate governance to the domain of supply chain resilience. Unlike most prior studies that emphasize analysts' forecasting roles, this paper underscores their influence at the supply chain level, where their monitoring and informational functions have direct implications for operational robustness. By reducing information asymmetry, constraining managerial opportunism, and shaping external stakeholders' perceptions of firm credibility, analysts contribute to a governance mechanism that strengthens firms' capacity to withstand and recover from external shocks. This reframing broadens the scope of existing literature and provides a novel mechanism through which analysts influence firm behavior, thereby enriching both supply chain management research and analyst-related studies. The findings highlight analysts as critical external actors who, by interpreting and disseminating information across financial and operational domains, help bridge the gap between capital markets and supply chain resilience.

In practice, the empirical results offer several important implications for firms navigating an environment of increasing uncertainty and policy emphasis on supply chain security. First, firms should recognize analyst coverage as a strategic resource that can enhance their resilience. To attract sustained analyst attention, companies are encouraged to improve the transparency and credibility of financial reporting, ensure consistency in operational disclosures, and adopt innovative technologies to enhance supply chain visibility and resource integration. By providing analysts with reliable and timely information, firms can foster more favorable evaluations, which in turn lower financing costs, strengthen investor confidence, and signal operational soundness to supply chain partners. Moreover, firms should actively strengthen their communication channels with analysts by holding regular earnings briefings, engaging in proactive investor relations activities, and maintaining open lines of dialogue. Such practices help ensure that analysts accurately understand firms' strategies, business models, and resilience-building efforts, thereby reinforcing the transmission of positive information to markets and stakeholders. Taken together, these measures enable firms not only to benefit from capital market advantages but also to build more robust, flexible, and adaptive supply chains.

Despite our contributions, we face several limitations that suggest directions for future research. First, the analysis is conducted in China, where government policies, state ownership, and financial market structures may uniquely shape the relationship between analyst coverage and supply chain resilience, raising concerns about generalizability. Second, supply chain resilience is conceptually complex and multidimensional, yet this study relies on proxies that may not fully capture firms' dynamic capacity to absorb, adapt, and recover from shocks. Future research could refine its measurement by using real-time operational data, supply network structures, or alternative indicators of adaptive capacity. By addressing these limitations, future studies could deepen our understanding of how analysts, as external information intermediaries and governance agents, enhance and influence firms' ability to sustain supply chain in global environments.

Appendix 1: Variable definitions

Dependent variable

Variable	Definition
SCR	Supply–demand volatility caused by the bullwhip effect. $-\frac{sd(Production)}{sd(Demand)} \times 100$, where $sd(\cdot)$ denotes the standard deviation computed over the current and previous four years, *Demand* is sales revenue, and *Production* equals *Demand* plus the change in net inventories.

Independent variable

Variable	Definition
Ln_coverage	Natural logarithm of one plus the number of analysts covering the firm each year

Control variables

Variable	Definition
Ln_assets	Natural logarithm of total assets.
Ln _age	Natural logarithm of one plus the difference between current year and listing year.
Leverage	Total liabilities divided by total assets.
ROA	Operating profit divided by total assets.
Return	Annual stock return accounting for cash dividend reinvestment.
Tobin_Q	Market value of assets divided by total assets.
CFO	Net cash flow from operating activities divided by total assets.
EBIT_volatility	Standard deviation of earnings before interest and taxes divided by total assets, calculated using the current and previous four years.
Z_score	$Z\_score = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$, where X_1 is net working capital divided by total assets, X_2 is accumulated retained earnings divided by total assets, X_3 is earnings before interest and tax divided by total assets, X_4 is market value of equity divided by book value of debt, and X_5 is operating revenue divided by total assets.
Ln_board	Natural logarithm of one plus the number of board directors.
Independence	Proportion of independent directors on the board.
Dual	A dummy variable equal to one if the board chairman also serves as the CEO, and zero otherwise.
Top1	Proportion of shares owned by the largest shareholder.
Inst	Sum of shares owned by institutional investors as a percentage of total shares outstanding.
Big4	A dummy variable equal to one if the audit is provided by the Big4 audit firm, and zero otherwise.

Other variables

Variable	Definition
ExpCoverage	Following Yu (2008), *ExpCoverage* is constructed as follows: $$ExpCoverage_{i,t} = \sum_{j=1}^{n} \left(\frac{Brokersize_{j,0}}{Brokersize_{j,t}}\right) \times Coverage_{i,j,0}$$ where $BrokerSize_{j,t}$ denotes the total number of analysts employed by brokerage firm *j* in year *t*, $BrokerSize_{j,0}$ is the number of analysts in the benchmark year, and $Coverage_{i,j,0}$represents the number of analysts from brokerage firm *j* covering firm *i* in the benchmark year.
Turnover	The average daily turnover rate during the year, calculated based on the total number of shares.
AEM	The absolute value of discretionary accruals estimated from the modified Jones (1991) model.
REM	Following *Roychowdhury (2006)*, real earnings management is measured by deviations from normal operating activities intended to influence reported earnings through real actions rather than accounting adjustments, and its absolute value is taken.
SA_index	$(-0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age)$, where $Size$ is the natural logarithm of total assets and Age is the difference between current year and founding year.
KZ_index	We construct *KZ_index* in three steps. First, we compute five ratios: net operating cash flows divided by total assets at the beginning of the year ($\frac{CF_{i,t}}{Asset_{i,t-1}}$), cash dividends divided by total assets at the beginning of the year ($\frac{Div_{i,t}}{Asset_{i,t-1}}$), cash and cash equivalents divided by total assets at the beginning of the year ($\frac{Cash_{i,t}}{Asset_{i,t-1}}$), total liabilities divided by total assets ($Lev_{i,t}$), and Tobin's Q ($Q_{i,t}$). For each year, and using the annual median, we define five indicator variables: if $\frac{CF_{i,t}}{Asset_{i,t-1}}$ is below the median, KZ_1 equals one, and zero otherwise; if $\frac{Div_{i,t}}{Asset_{i,t-1}}$ is below the median, KZ_2 equals one, and zero otherwise; if $\frac{Cash_{i,t}}{Asset_{i,t-1}}$ is below the median, KZ_3 equals one, and zero otherwise; if $Lev_{i,t}$ is above the median, KZ_4 equals one, and zero otherwise; and if $Q_{i,t}$ is above the median, KZ_5 equals one, and zero otherwise. We then calculate KZ as the sum of these five indicator variables. Second, we estimate the following ordered logistic regression:$KZ_{i,t} = \alpha_1 \times \frac{CF_{i,t}}{Asset_{i,t-1}} + \alpha_2 \times \frac{Div_{i,t}}{Asset_{i,t-1}} + \alpha_3 \times \frac{Cash_{i,t}}{Asset_{i,t-1}} + \alpha_4 \times Lev_{i,t} + \alpha_5 \times Q_{i,t}$. Third, *KZ_index* is the fitted value computed using the estimated coefficients.
SCR_3	Supply–demand volatility caused by the bullwhip effect. $-\frac{sd(Production)}{sd(Demand)}/100$, where $sd(\cdot)$ denotes the standard deviation computed over the current and previous two years, *Demand* is sales revenue, and *Production* equals *Demand* plus the change in net inventories.
SCR_7	Supply–demand volatility caused by the bullwhip effect. $-\frac{sd(Production)}{sd(Demand)}/100$, where $sd(\cdot)$ denotes the standard deviation computed over the current and previous six years, *Demand* is sales revenue, and *Production* equals *Demand* plus the change in net inventories.
Ln_report	Natural logarithm of one plus the number of research reports issued by analysts covering the firm.
SCC	The average of the proportion of sales to the top five customers in total annual sales and the proportion of purchases from the top five suppliers in total annual purchases.
CR	A unit interval variable. If any of the top five customers change, the value decreases by 0.2 (i.e., two changes result in –0.4, and so on, until it reaches 0). If there is no change, the value remains 1.

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