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ANCHORING THE CHAIN: THE STABILIZING EFFECT OF BLOCKCHAIN TECHNOLOGY ON SUPPLY CHAIN VOLATILITY

Master Thesis

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Declaration

I have written this Master Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

In the preparation of this Master's thesis, I used the generative artificial intelligence tool Claude as a supporting aid. The tool was used for the following purposes only: improving the clarity, grammar, and readability of text originally drafted by me; assisting with translating the abstract and keywords into Estonian; and assisting with debugging the code used for data processing and empirical analysis.

Artificial intelligence was not used to generate the research design, collect or analyse the data, produce the empirical results, or formulate the original arguments, findings, and conclusions of this thesis. All substantive content, interpretations, and intellectual contributions are my own.

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Abstract

Although blockchain is widely promoted as a tool for strengthening supply chain resilience, rigorous firm-level evidence on whether it actually stabilizes supply chains — and through which channels — remains scarce. Using text mining of the annual reports of Chinese A-share listed firms from 2017 to 2024, we construct a TF-IDF-weighted index of blockchain strategic disclosure and a new dynamic measure of supply chain volatility based on year-on-year shifts in a firm's partner transaction structure. We estimate two-way fixed-effects models and apply an instrumental-variable strategy to address potential endogeneity. We find that greater blockchain disclosure is robustly associated with lower supply chain volatility, with the stabilizing effect noticeably stronger on the supplier side than on the customer side. This effect operates through two channels including lower administrative expense ratios (a managerial efficiency channel) and broader partner diversification (a structural channel), and is strongest precisely where market frictions are greatest, namely under high environmental uncertainty and intense competition, though it weakens for resource-constrained firms. These results indicate that blockchain is not merely a passive record-keeping tool but a strategic capability that helps firms anchor their supply chains against shocks, implying that managers and policymakers should direct adoption support toward high-uncertainty environments and financially constrained firms.

Keywords: blockchain technology, supply chain volatility, supply chain resilience, text mining, dynamic capabilities

Resümee

KETI ANKURDAMINE: PLOKIAHELA TEHNOLOOGIA STABILISEERIV MÕJU TARNEAHELA VOLATIILSUSELE

Zhongyi Pan

Kuigi plokiahelat propageeritakse laialdaselt kui vahendit tarneahela vastupidavuse tugevdamiseks, napib endiselt rangeid ettevõtte tasandi empiirilisi tõendeid selle kohta, kas plokiahel tegelikult stabiliseerib tarneahelaid ning milliste kanalite kaudu see toimub. Kasutades Hiina A-aktsiate nimekirja kuuluvate ettevõtete aastaaruannete tekstikaevet aastatel 2017–2024, koostame plokiahela strateegilise avalikustamise TF-IDF-kaalutud indeksi ning uue tarneahela volatiilsuse dünaamilise mõõdiku, mis põhineb ettevõtte partnerite tehingustruktuuri aastastel muutustel. Me hindame kahesuunalise fikseeritud efektiga mudeleid ning rakendame instrumentaalmuutuja strateegiat, et käsitleda võimalikku endogeensust. Me leiame, et ulatuslikum plokiahela avalikustamine on robustselt seotud madalama tarneahela volatiilsusega, kusjuures stabiliseeriv mõju on märgatavalt tugevam tarnijate poolel kui klientide poolel. See mõju avaldub kahe kanali kaudu — madalamad halduskulude määrad (juhtimise tõhususe kanal) ja partnerite laiem mitmekesistamine (struktuurne kanal) — ning on kõige tugevam just seal, kus turutõrked on suurimad, nimelt suure keskkonna ebakindluse ja tiheda konkurentsi tingimustes, kuigi see nõrgeneb piiratud ressurssidega ettevõtete puhul. Need tulemused näitavad, et plokiahel ei ole pelgalt passiivne andmete salvestamise vahend, vaid strateegiline võimekus, mis aitab ettevõtetel ankurdada oma tarneahelaid šokkide vastu; see viitab sellele, et juhid ja poliitikakujundajad peaksid suunama tehnoloogia kasutuselevõtu toetuse suure ebakindlusega keskkondadesse ja finantsiliselt piiratud ettevõtetele.

Märksõnad: plokiahela tehnoloogia; tarneahela volatiilsus; tarneahela vastupidavus; tekstikaeve; dünaamilised võimekused

Introduction

According to the World Meteorological Organization (2021), the frequency of sudden and damaging events has increased greatly over the past five decades. The Global Assessment Report published by the United Nations Office for Disaster Risk Reduction (2022) also predicts that up to 560 large-scale disasters may occur every year by 2030. As systemic shocks continue to increase, they have strongly exposed the basic weaknesses of supply chain structures. The COVID 19 pandemic, together with other events such as the Fukushima disaster and disruptions in the Strait of Hormuz, are clear examples that caused serious damage to production and logistics networks (Govindan et al., 2020; Lin & Zhang, 2025; Paul & Chowdhury, 2020; United Nations, 2020). These disruptions show that most existing supply chains lack the adaptive capacity to absorb repeated shocks, which allows local disruptions to spread into systemic and cross-border damage (Ivanov, 2024a; Shi et al., 2022).

To address this structural weakness, supply chain resilience has become a core strategic priority (van Hoek, 2020a). It is defined as the ability to predict unexpected disruptions, absorb their impacts, and recover to the original or a higher level of performance (Hohenstein et al., 2015). As researchers have made greater efforts to explore mechanisms for improving resilience, digital technologies have received particular attention (Ivanov et al., 2019a; Spieske & Birkel, 2021). Among these technologies, blockchain technology has special advantages because it can improve managerial efficiency and promoting diversification that exist in complex supply chain networks (Lim et al., 2021; Y. Wang et al., 2018). As a decentralized distributed ledger, blockchain uses timestamps, consensus mechanisms, and encryption algorithms to ensure information integrity, transparency, and traceability (Fosso Wamba et al., 2020; Nakamoto, 2008). These features make real time information sharing, automatic contract execution through smart contracts, and end to end goods tracking among supply chain members possible (Luo & Choi, 2024; Pettit et al., 2019). Early industrial applications have shown these features. Maersk and Walmart used blockchain to improve supply chain transparency, while Daimler simplified financing processes through blockchain supported smart contracts (Dubey et al., 2020a; Lohmer et al., 2020). This suggests that the governance value of this technology extends from contract clarity to operational transparency across the whole supply chain. Theoretically, the built in features of blockchain can reduce trust frictions, support collaborative decision-making, and weaken the bullwhip effect by sharing accurate demand signals with upstream firms. In this way, blockchain can help buffer supply chains against crises (Dubey et al., 2019; Mukherjee et al., 2022).

However, although blockchain research has grown rapidly, most supply chain-related studies still remain at the stage of qualitative discussion or conceptual modeling (Beck et al., 2023; Manzoor et al., 2024; Pattanayak et al., 2024). In addition, the limited related empirical analyses mainly focus on performance outcomes(Sheel & Nath, 2019; Vazquez Melendez et al., 2024), while empirical research on the micro-level causal relationship between blockchain and supply chain resilience is still limited.

This scarcity is reflected in three specific and interconnected aspects. First, at the explanation level, previous empirical studies treated blockchain adoption as a simple binary choice in which firms either use the technology or do not use it (R. Li & Wan, 2021). As a result, they ignored the strategic and gradual process of blockchain adoption within firms. Second, at the outcome level, resilience has been repeatedly mentioned as a dependent variable, but it has rarely been operationalized as a dynamic, micro level, and time varying indicator (Peng et al., 2020). Third, regarding contingency factors, previous findings remain inconsistent and no common conclusion has been reached (Babich & Hilary, 2020a; Klöckner et al., 2022). This situation leaves scholars and practitioners without reliable guidance to determine when, how, and for which groups blockchain can generate its promised stability benefits.

This measurement problem is acute. Unlike previous quantitative studies that use questionnaire surveys of supply chain professionals(Sheel & Nath, 2019), this paper argues that firm-level technology upgrading requires strategic attention from management and clear signals from the firm. In a highly regulated corporate environment, frequent disclosure of blockchain strategy in annual reports is a costly and audited signal of a firm's commitment to supply chain transparency. Guided by the attention-based view (ABV), and signaling theory, this study explains how this ex ante strategic positioning can reduce compliance risk and build mutual trust among supply chain nodes. Mutual trust is a necessary institutional condition for actual technology implementation.

In addition, this study contributes a measurement strategy by treating supply chain volatility (SCV) as an observable, structural proxy for one dimension of supply chain resilience. Resilience is a latent, dynamic organisational capability that cannot be measured directly; its micro-level footprint, however, is visible in the year-on-year stability of a firm's partner transaction structure. This study therefore constructs a dynamic volatility index from the Euclidean distance between consecutive-year partner transaction-share vectors, and interprets lower volatility as consistent with higher realised resilience. The proxy captures the structural-stability dimension of resilience, not the full latent construct.

Synthesizing these tracks, the core research question of this paper is how firms' strategic positioning in blockchain technology can be translated into micro level supply chain resilience. This question is decomposed into three sub questions: whether greater blockchain disclosure predicts lower volatility; whether the effect is asymmetric between the supplier and customer sides; and through which channels and under which conditions it is more pronounced.To answer this question, this study follows Xiong et al. (2025) and applies text mining techniques to the annual reports of Chinese A share listed firms from 2017 to 2024, constructing a TF IDF weighted index of blockchain related disclosure intensity that resolves the scalability problem in the absence of a dedicated database. It should be acknowledged that ln_TFIDF_BC captures firms' strategic and text based disclosure of blockchain rather than direct software installation. This is a deliberate design choice that is consistent with signaling logic, and its limitations are addressed through an instrumental variable strategy. A two-way fixed-effects model is employed for the baseline regression analysis, and an instrumental variable approach is further applied to alleviate potential endogeneity problems.

The analysis produces four main findings. First, The results show a robust within-firm association between blockchain-related disclosure intensity and lower supply-chain volatility. Because the instrumental-variable design is weak and does not support causal inference, the findings should be interpreted as conditional associations rather than causal effects. The upstream effect is consistently stronger than the downstream. Second, this stabilizing effect is consistent with two related channels. The first is the managerial efficiency channel, which works through lower administrative expense ratios. The second is the structural optimization channel, which works through supply chain diversification. Third, the strength of this relationship depends on the context. It becomes stronger under high environmental uncertainty, in more competitive markets, and with mixed evidence on the role of complementary AI capability. Finally, the acid test confirms that the effect becomes stronger exactly when market friction is the greatest.

Second, this study operationalises a dynamic, firm-level measure of supply chain volatility that serves as an observable structural proxy for one dimension of resilience, complementing rather than replacing survey and concentration-based measures.

Second, this study operationalizes a dynamic firm level measure of supply chain volatility. By treating dynamic partner turnover and transaction share fluctuations as the inverse proxy of shock absorption capability, this study proxy for the structural-stability dimension of resilience.

Third, this study reframes the sample's data constraints as a stress test opportunity and develops a Pressure-Capability-Match framework (PCM). By observing firm performance in high friction and high competition environments with a low Herfindahl Hirschman Index, the significant interaction term directly confirms the dynamic resilience of blockchain, in which firms become stronger under greater pressure. This finding shows that the stability effect is not random. Instead, it is a key dynamic capability shown by firms when they face serious environmental threats.

The remainder of this thesis is organized as follows. Chapter 1 reviews the literature on supply chain resilience and blockchain technology and develops six hypotheses. Chapter 2 describes the data, sample construction, and measurement of the main variables. Chapter 3 explains the empirical strategy, including the baseline model and the identification approach. Chapter 4 presents descriptive evidence on blockchain diffusion and the structural features of supply chain volatility. Chapters 5 to 7 report three groups of findings, including the main stabilizing effect, the transmission channels, and the boundary conditions. The study concludes with theoretical contributions, practical implications, limitations, and directions for future research.

1. Literature review

As one of the most serious supply chain interruptions in modern history, the operation of supply chains in various regions has been affected (Ivanov & Dolgui, 2020a), resulting in greater demand uncertainty, serious shortages of raw materials and labour, and severe restrictions on transportation. At the same time, there has been a significant decline in production capacity (Sarkis, 2020). At the same time, it has also aroused researchers' unprecedented attention to the global supply chain, which fundamentally prompts researchers to re-examine and think about the existing supply chain resilience reinforcement paradigm, so as to alleviate the unfavourable situation and ensure the continuity of operations(Modgil et al., 2021; van Hoek, 2020b). In the face of this highly dynamic and changing environment, the study believes that serious interruptions force enterprises to adopt new methods and technologies to survive (Shen & Sun, 2023). Based on this, this literature review will focus on the intersection of the three fields of supply chain resilience, supply chain risk management and blockchain technology. Based on the existing theory, the research gap will be further analysed (Seuring & Gold, 2012).

1.1 Theoretical Framework

1.1.1 Dynamic Capabilities View

The Dynamic Capabilities View (DCV) provides the overarching theoretical architecture for this study. Teece (2007, p. 1319) defined dynamic capabilities as ’the capacity to sense and shape opportunities and threats, to seize opportunities, and to maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise’s intangible and tangible assets.’ The three-stage sense – seize – reconfigure logic maps onto the SCR literature’s anticipation – absorption – recovery cycle: sensing corresponds to proactive monitoring and early detection of upstream or downstream stress signals; seizing corresponds to real-time absorption of disruptions through rapid resource deployment and partner coordination; reconfiguring corresponds to post-disruption structural recovery and network redesign that restore operational continuity.

The DCV’s positioning of the organizational rather than the technological as the unit of analysis is critical for this study. Blockchain, in the DCV framework, is not itself a dynamic capability but rather a technological infrastructure that enables the deployment of dynamic capabilities by providing the information coherence without which sensing and reconfiguring cannot be performed efficiently. This distinction implies that blockchain’s supply chain benefits will be realized only by firms that possess the organizational routines, partner governance structures, and managerial processes necessary to leverage blockchain's informational advantages — explaining why the same technology generates heterogeneous outcomes across firms (Culot et al., 2024; Dong et al., 2025).

Schilke's (2014) formalization of the DCV's contingency proposition is the foundational premise of the boundary condition framework developed in Section 1.8. Through nonlinear analysis of the environmental dynamism – performance relationship, Schilke demonstrated that dynamic capabilities deliver competitive advantage primarily in moderately to highly dynamic environments: in stable environments, the continuous overhead of capability deployment may exceed the infrequent benefits from disruption absorption. This contingency pattern directly motivates the pressure-dimension hypothesis (H4) and grounds the empirical expectation that blockchain's supply chain stabilization effect should be amplified in high-uncertainty, high-competition contexts.

More recent DCV scholarship has extended Teece's framework to incorporate digital technologies as the contemporary mechanisms of dynamic capability deployment. Ivanov and Dolgui (2020) developed a supply chain viability framework in which blockchain, AI, and IoT serve as sensing-and-reconfiguring infrastructure, enabling firms to detect supply chain disruptions in real time and coordinate responses across multiple tiers simultaneously. Dubey et al. (2023) provided panel-based empirical support, demonstrating that digital dynamic capabilities are associated with lower disruption frequency, with the association strengthened under higher environmental uncertainty. Dolgui and Ivanov (2021) demonstrated that blockchain-coordinated supply chains exhibit greater resistance to ripple effects consistent with DCV's prediction that dynamic capabilities reduce systemic amplification of local shocks. Ivanov (2024b) examined how supply chain resilience research itself was transformed by COVID-19, documenting the shift from static structural analysis toward dynamic viability frameworks.

A critical theoretical contribution of the DCV perspective is its implication for how resilience should be operationalized in archival panel research. Because DCV frames resilience as a dynamic process rather than a static structural state, it logically implies that resilience should be measured through the dynamics of supply chain behavior rather than through cross-sectional snapshots of network topology. Ivanov (2024c) made this implication explicit, arguing that panel-based volatility measures better capture the dynamic capability logic of resilience than structural proxies and that behavioral, process-based measures are more theoretically consistent with DCV.

This DCV-derived implication provides the theoretical foundation for the SCV measure. Under DCV logic, a firm with high dynamic resilience capability maintains stable supply chain partnerships under moderate environmental stress. Its supply chain volatility is consequently low. Conversely, a firm with low dynamic resilience capability lacks the routines needed to absorb shocks within existing structures; instead, it resolves disruptions through reactive partner substitution all of which manifest as elevated year-on-year volatility in partner revenue share distributions. This operationalization offers four advantages over existing approaches. First, it is dynamic: it captures temporal variation in supply chain behavior rather than cross-sectional snapshots. Second, it is objective: derived from audited financial disclosures rather than managerial self-report. Third, it is theoretically grounded: its interpretation as a resilience indicator follows directly from DCV's process logic. Fourth, it is directionally decomposable: SCV can be computed separately for supplier-side and customer-side relationships. Zhao et al. (2023) and Ming et al. (2025) provide convergent empirical validation, demonstrating that digitalization-driven reductions in year-on-year supply chain partner relationship volatility are associated with improved supply chain performance outcomes. Jiang et al. (2023) further confirmed that temporal stability in supply chain partner distributions is a meaningful indicator of underlying resilience capability: firms with higher pre-pandemic supply chain relationship stability exhibited superior COVID-19 resilience. Smyth et al. (2024) and Ivanov and Dolgui (2021) similarly advocate for dynamic performance metrics that capture adaptation trajectories, reinforcing the SCV operationalization's theoretical legitimacy.

1.1.2 The Attention-Based View

Operationalizing blockchain strategic positioning for large-panel archival research presents a challenge symmetric to the one identified for supply chain resilience. Blockchain adoption is not a discrete event that can be cleanly dated; it unfolds progressively through strategic planning, investment commitment, partner negotiation, technical integration, and organizational adaptation (Stratopoulos et al., 2022). The binary survey indicators common in the literature (Dong et al., 2025; Sharma et al., 2023) capture only whether a firm has crossed some self-reported adoption threshold, losing the continuous variation in commitment intensity that is theoretically essential. Sheel and Nath (2019) documented the limitations of questionnaire-based adoption measures, showing that supply chain blockchain studies relying on binary self-report found inconsistent results precisely because the heterogeneity in adoption depth is collapsed by binary coding. Event-study binary proxies (Klöckner et al., 2022) capture announcement timing but cannot represent the sustained strategic commitment that DCV predicts to be the mechanism of resilience improvement. Two theoretical frameworks resolve this challenge.

Ocasio (1997) positioned managerial attention as the firm's most fundamental scarce resource. In the ABV framework, organizations perceive and respond only to opportunities and threats that have captured the sustained, channeled attention of their senior decision-making hierarchy; all other signals are filtered out by the cognitive and organizational routines that structure what leaders notice, encode, and act upon. Strategic attention is not merely a cognitive state but a social-organizational phenomenon: it is allocated through formal reporting structures, governance routines, and communication channels that create what Ocasio (1997, p. 189) termed 'a structured repertoire of patterned, directed attention.' Strategic priorities that receive sustained attention become embedded in organizational routines, resource allocation processes, and communication patterns; those that do not receive attention remain marginal regardless of their theoretical merit.

Applied to annual report disclosures, ABV implies that the depth and consistency with which a firm's senior leadership discusses blockchain across its 10-K or 20-F filing reveals the degree to which blockchain has captured sustained, organization-level strategic attention. A firm that mentions blockchain once in a generic risk factor disclosure is signaling exploratory awareness; a firm that discusses blockchain strategy, operational implementation, capital expenditure allocation, and risk factor implications across multiple sections is exhibiting the structured, cross-functional attention allocation that, under ABV logic, is both a necessary precursor to resource commitment and a reliable indicator of existing strategic commitment. Stratopoulos et al. (2022) operationalized this insight, finding that textual disclosure depth across annual report sections reliably discriminates among blockchain adoption stages verified through independent corroborating sources.

1.1.3 Signaling Theory

Spence (1973) established the conditions under which observable actions can credibly convey private information to uninformed counterparties in markets characterized by information asymmetry. For a signal to be credible in equilibrium, it must be costly enough to produce that low-type senders cannot costlessly mimic high-type senders, and the cost must be differentially borne by those who lack the underlying quality being signaled. Connelly et al. (2011) synthesized signaling theory in a management context, confirming that signal cost and signal observability are the two critical determinants of credibility across organizational communication contexts.

Annual report disclosures in regulated capital market environments satisfy both conditions with unusual rigor. First, they are costly: the preparation of audited financial statements requires significant legal, accounting, and executive resources, and false or misleading disclosures trigger regulatory liability under securities law. Second, the cost is differentially borne by firms with low genuine blockchain commitment: a firm that prominently positions blockchain strategy across its annual report without genuine operational commitment is exposed to escalating reputational and regulatory risk as the discrepancy between claimed capability and observed operational outcomes becomes apparent to analysts, investors, and auditors in subsequent reporting periods. Sustained, high-intensity, multi-section blockchain disclosure in annual reports is therefore not cheap talk—it is a costly, audited signal that credibly commits the firm to a blockchain-consistent operational trajectory. Yavaprabhas et al. (2023) corroborate this in their trust-transfer analysis, finding that disclosure-based trust signals are credible precisely because they are embedded in formal reporting structures with institutional enforcement mechanisms. Autore et al. (2024) provided complementary evidence that blockchain adoption signals in financial disclosures have material information content that sophisticated investors distinguish from superficial claims.

1.2 Blockchain Technology

This section reviews the theoretical essence, evolution stage, core characteristics and application status of blockchain technology in various fields. Then, in combination with the specific context of China's capital market, this study deeply explores the development characteristics of blockchain concept stock listed companies. The above combing and exploration lay the theoretical foundation for the subsequent analysis of how blockchain applications affect the resilience of the supply chain.

Essentially, blockchain is a decentralized distributed ledger, while smart contracts are self-executing protocols running atop it, with terms and conditions directly embedded in the code . Blockchain technology was initially proposed by Satoshi Nakamoto (Nakamoto, 2008)in a research report as the underlying architecture for Bitcoin. From a technical logic perspective, it is a data structure that stores information in units of blocks and forms a chain through cryptographic means. From an economic logic perspective, it is an Internet-of-Value protocol that solves data trust issues. According to differences in consensus algorithms and access mechanisms, blockchain can be divided into public chains, private chains, and consortium chains. Among them, the consortium chain, as a semi-open architecture requiring registration and permission, has its consensus process controlled by pre-selected nodes. Due to its high requirements for security and performance, it is widely applied in B2B scenarios such as inter-institutional transactions, settlement, or clearing (Yermack, 2017).

According to the logic of technical evolution, blockchain has progressed through the programmable currency stage (Blockchain 1.0), the programmable finance stage (Blockchain 2.0), and the current 3.0 stage, which is transitioning toward a programmable society (Tapscott & Tapscott, 2018). In the current transition period, blockchain has penetrated fields such as supply chains, healthcare, and smart cities wherever demand exists. Schmidt & Wagner (2019a) focused on its immutability and automated execution features, demonstrating how this technical essence fundamentally changes supply chain governance structures, distinguishing them from traditional IT systems that rely on centralized authorization.

This reconstruction of governance logic primarily stems from the following six core characteristics. First is decentralization, where blockchain establishes a distributed ledger system to achieve direct peer-to-peer interaction and build trust relationships among multiple nodes, eliminating the risk of fraud by central institutions (Schmidt & Wagner, 2019a). Second is traceability, as blockchain adds a time-dimension attribute to data through its chain structure, ensuring all transaction records can be traced and viewed. Third is immutability; modifying block data requires altering all full nodes, and this immense cost guarantees the authenticity of information. Fourth is the distributed ledger characteristic, which is an asset database shared simultaneously across different locations, solving the problem of data matching and interoperability between different institutions and significantly increasing the degree of security. Fifth is the smart contract program; as script code deployed on the chain, it executes automatically once established terms are triggered, simplifying business processes and achieving credible sharing between untrusting parties. Finally is the consensus mechanism, which ensures all nodes participate in the verification process of data blocks through a unified algorithm. Overall, these studies indicate that the application of blockchain is reshaping the interaction logic among supply chain members.

Many studies discuss the potential benefits or advantages of adopting blockchain technology (Babich & Hilary, 2020b; K. Li et al., 2023; Lumineau et al., 2021). In the financial field, blockchain is considered to have disruptive transformative capabilities (Treleaven et al., 2017), creating a secure and creative digital platform for the financial industry (Ali et al., 2017). Song et al. (2019) revealed innovative applications of blockchain in direct financing, bank credit, and supply chain finance scenarios. In supply chain management practice, blockchain's ability to induce business model transformation has been recognized (Tandon et al., 2020). Specifically, integrating blockchain into supply chain architecture can create a reliable, transparent, and secure system (Azzi et al., 2019), thereby improving operational efficiency and information security. Cole et al.(2019a) argued that blockchain can change practices in various ways, including improving quality management, reducing illicit counterfeiting, optimizing sustainable supply chain management, advancing inventory replenishment, reducing the need for intermediaries, and lowering supply chain transaction costs. Research by Zhang et al. (2024) also shows that blockchain platforms can significantly promote corporate emission reduction and enhance social welfare. Furthermore, blockchain's impact on corporate governance is equally profound. As a new method for tracking ownership, it ensures record accuracy and ownership transparency (Yermack, 2017).

Conversely, other studies examine the realistic obstacles and challenges in blockchain implementation (Schmidt & Wagner, 2019a; M. Wang et al., 2020). Enterprises may face resistance from managerial self-interest during the adoption process, resulting in the technology failing to translate into substantive governance effectiveness (M. Wang et al., 2020). Schmidt and Wagner (2019a) also found that differences in the effectiveness of internal governance mechanisms and implementation risks brought by environmental uncertainty cause the empowering effect of blockchain to vary significantly across enterprises.

Although the rapid development of digital and intelligent technologies (Wu et al., 2016) is triggering a management revolution, and scholars have begun to explore the potential of the Internet of Things, big data, and cloud computing in enhancing stability (Belhadi et al., 2021; Katsaliaki et al., 2022), in-depth analysis of these emerging technologies remains scarce. Existing understanding of the impact of adopting blockchain technology on specific firm-level operational outcomes, particularly on supply chain stability, remains limited. Furthermore, most existing studies focus on theoretical modeling and conceptual analysis, while empirical evidence is relatively scarce. Therefore, this paper aims to empirically test how blockchain technology affects supply chain stability, thereby revealing whether it can truly help enterprises achieve the enhancement of supply chain stability.

1.3 Conceptualizing Supply Chain Risks

The conceptualisation of supply chain risks has a long history in supply chain risk management research (Rangel et al., 2015). Supply chain risk refers to the mismatch between supply and demand (Jüttner et al., 2003). More specifically, risk is defined as an event that adversely affects supply chain operations and its expected performance indicators (Tummala & Schoenherr, 2011, p. 474). This definition reflects the two main perspectives adopted by scholars when conceptualising supply chain risks.

On the one hand, the researchers analysed the consequences of supply chain risks. This kind of analysis is important because the main job of the supply chain risk management system is to mitigate the negative consequences caused by unfavourable events (Hosseini et al., 2019). The negative effects of supply chain risks include declines in revenue, damage to market share, loss of reputation, and increased costs. These problems often arise because customer needs are not met (Dolgui et al., 2018; López & Ishizaka, 2019).

On the other hand, scholars classify risks according to their causes. Some people adopt the internal perspective of the supply chain to pay attention to events that directly affect the flow of goods, information and money (Manuj & Mentzer, 2008; O. Tang & Nurmaya Musa, 2011). Among them, the more well-known classifications come from Manuj and Mentzer (2008). They distinguish between four types of supply chain risks, namely supply risk, operational risk, demand risk and security risk. Many researchers have expanded the original classification by adding external risks, including macro risks, destructive risks, environmental risks or catastrophic risks, based on this classification (Ho et al., 2015; Rangel et al., 2015). Natural disasters, economic recessions, political uncertainty and terrorist attacks are all examples of external risks (Ivanov et al., 2019b; Rao & Goldsby, 2009; C. S. Tang, 2006). Compared with internal risks, such external risks are more unpredictable, and their consequences are often disastrous (Bayramova et al., 2021). In addition, although the original classification of Manuj and Mentzer (2008) did not explicitly mention sustainability risks, the discussion in this area has increased significantly in recent years (M. Xu et al., 2019). However, Manuj and Mentzer (2008, p. 138)point out that there is a cross between different types of risks. They overlap each other, do not exist in isolation, and often appear in the form of a combination of supply, demand, operational and security risks. Hall (2006) and Canzaniello, Hartmann and Fifka (2017)also support this view. They pointed out that the poor performance of suppliers in terms of sustainability can easily become a supply risk for buyers. Similarly, Rao and Goldsby (2009) believe that natural disasters threaten operational activities and therefore constitute a serious operational risk.

1.4 Supply Chain Resilience and Volatility

In the contemporary context of corporate management, supply chain configuration represents both an extension of internal resource allocation and a strategic core for addressing the global dynamic competitive environment. Traditional research has long focused on enhancing operational efficiency through structural optimization, with its economic consequences empirically validated across dimensions such as corporate performance, investment efficiency, financing pathways, and the quality of accounting information disclosure (Christopher & Holweg, 2011).

However, following the frequent occurrence of external environmental shocks such as natural disasters and public health crises (Ivanov & Dolgui, 2020a), coupled with intensifying global trade conflicts, the academic focus has shifted significantly from pure efficiency-seeking to the maintenance of supply chain stability, with dynamic resilience emerging as a central strategic priority. Scholars and practitioners have gradually realised that supply chain resilience plays a key role in maintaining or gaining competitive advantages during supply chain interruption (Dubey et al., 2021). Tukamuhabwa et al. (2015a) regard resilience as a key characteristic that the supply chain needs to have, and its role is to reduce financial and operational losses caused by interruption. In addition, toughness is established as a dynamic structure, not a static structure (Ali et al., 2017).

From a positive perspective, the blockchain-powered supply chain can improve multiple performance indicators, including supply chain relationships, product safety, process efficiency, transaction costs and order time (Queiroz et al., 2019; Saberi et al., 2019; Schmidt & Wagner, 2019b; Wamba & Queiroz, 2022). Furthermore, research by Rejeb et al. (2021) and Schmidt and Wagner (2019a) shows that blockchain technology can enhance the collaborative ecosystem. And the transparency of blockchain also helps the network to build stronger trust (Dubey et al., 2019, 2020b; P. Xu et al., 2021). In terms of risk management, Hastig and Sodhi (2020) pointed out that blockchain technology can identify emergencies as early as possible by tracking real-time transactions. During the shortage period, the blockchain-powered supply chain can help identify alternative sources of supply (Kamble et al., 2021). Xiong et al.(2021) as well as Schmidt and Wagner(2019a) pointed out that smart contracts can ensure timely payment and avoid default. However, the key problem is that the blockchain characteristics mentioned in the literature (Babich & Hilary, 2020b) are well understood alone. However, their overall relationship with the resilience of the supply chain and the importance of resilience have not been fully empirically analysed.

Despite the depth of existing literature on supply chain resilience and its consequences, the vast majority of research regarding stability remains anchored in a static perspective(Tao et al., 2023). Currently, academia predominantly utilizes supplier concentration as a metric to capture the distribution of suppliers at a single point in time. While this provides a quantitative description of the supplier base, it largely ignores the dynamic evolution and real-time adjustments of the supply chain under complex environments. Specifically regarding blockchain technology, although its decentralized, immutable, and self-executing characteristics can strengthen collaborative relationships, limit opportunism, and optimize operational capabilities, it is regrettable that due to the relatively short period of blockchain application in supply chains, research exploring how blockchain stabilizes the supply chain through governance mechanisms is still in its infancy(Wamba & Queiroz, 2020).

Furthermore, many studies on the role of blockchain technology in the supply chain are limited to the conceptual level. From a practical point of view, these studies focus more on normative than exploratory or empirical rigour (Schmidt & Wagner, 2019a; Y. Wang et al., 2018). In addition, research by Frizzo-Barker et al. (2020) shows that only 6% of previous BCT studies have clearly focussed on the supply chain field. Even in this few research fields, its methodological tools are very limited; only a few studies use qualitative tools such as interviews for data collection. The existing literature mainly relies on use case guidance and theoretical modelling, rather than a robust large-sample econometric evaluation.

This neglect of dynamic changes and the governance mechanisms of cutting-edge technologies represents a primary gap in the current body of literature, highlighting the urgent need for studies that move beyond static concentration metrics and embrace the dynamic, technology-enabled evolution of supply chain resilience.

Hypothesis 1. The application of blockchain technology improves supply chain stability.

1.5 Informative Mechanisms

More importantly, the efficient physical flow (Umar & Wilson, 2024), unobstructed information flow (Lee et al., 1997), and deep financial flow(Ersahin et al., 2023) constitute the three essential pillars for sustaining supply chain equilibrium. Information flow is the heart of supply chain management. Problems such as lack of transparency and delays are the root causes of supply chain disruptions. In traditional management, information asymmetry between upstream and downstream firms is common. This leads to higher management costs and supply chain fluctuations. On the demand side, information is often filtered or magnified as it moves through different levels. This creates the bullwhip effect. It results in disorganized production and unbalanced supply and demand. These issues can lead to the failure of specific nodes or the entire chain (K. Li et al., 2023). On the supply side, incomplete contracts create risks. When contracts cannot cover all future situations, firms may act in their own interest. This erodes cooperation. Frequent audits and high inventory levels then become necessary, which leads to high costs (Katsaliaki et al., 2022).

Blockchain technology provides a systematic solution to these problems. First, it acts as a tool for contract execution (Babina et al., 2024). Its smart contracts turn agreement terms into self-executing code. When certain conditions are met, payments and ownership transfers happen automatically. This reduces the time and money spent on negotiations and enforcement. Second, the transparent ledger of blockchain makes transaction data visible to all authorized members. This removes the information gaps that cause the bullwhip effect (Richey Jr. et al., 2023). When all partners use the same shared record, demand signals become more accurate. This leads to better inventory planning and more stable operations. Additionally, smart contracts handle small or temporary transactions efficiently. They reduce the need for human supervision and lower costs (Walter et al., 2025). Finally, blockchain can provide early warning signals. Firms can use these signals to stop risks before they become full disruptions (Allal-Chérif et al., 2021).

In summary, blockchain improves stability by smoothing the flow of information. It lowers costs through smart contracts and reduces the bullwhip effect through shared ledgers. It also stops disruptions via early warnings. These factors make supply chain operations more predictable.

1.6 Structural Mechanisms

Diversification is another way to improve supply chain resilience. Research shows that relying on a few partners makes a firm vulnerable. Without alternative suppliers, a firm cannot easily adapt to internal or external shocks (Modgil et al., 2021). This is a major issue in the current global environment. Many firms are too concentrated in specific regions. Under traditional systems, finding new partners across borders is difficult. It requires high costs to build trust and integrate different types of knowledge (Haefner et al., 2021).

Blockchain helps firms overcome the habit of searching only in local or familiar areas. It provides a way to expand supply chain boundaries. First, blockchain uses distributed consensus to establish trust. This allows firms to work with partners regardless of geography or existing relationships (Babina et al., 2024). Second, the transparent records on the blockchain create a new type of credit profile. This profile is based on actual behavior rather than just identity. Firms can use this data to evaluate new and diverse partners (J. Liu et al., 2020). With this mechanism, firms can confidently find suppliers in distant locations. This reduces concentration and builds a more diverse network.

Diversification is a structural change from dependence to collaboration. Empirical data from Chinese manufacturing firms shows that diversification helps blockchain improve flexibility (Ren & Li, 2025). This suggests that blockchain increases stability by helping firms move beyond their fixed supply circles. It creates a network that can better spread risks.

Hypothesis 2. Blockchain technology enhances supply chain stability by improving managerial efficiency and promoting diversification.

1.7 Directional Differences in Blockchain Stability Effects

Blockchain generally improves stability but its effects may differ across supply chain relationships. Recent studies highlight this asymmetry. For example, blockchain adoption can improve the flexibility of both suppliers and customers. However, its effect on stability is different for each group. It often enhances the stability of the focal firm but may have a different impact on downstream customers(Ren & Li, 2025). Specifically, the positive effect is usually stronger for upstream suppliers.

There are logical reasons for this difference. Upstream management often faces problems like unverified material quality and uncertain delivery times. Blockchain solves these through traceability and automated settlements via smart contracts. It is easier to create a closed loop of transparency for supply management. In contrast, downstream customers face unpredictable market demand. While blockchain can reduce the bullwhip effect, it cannot remove the basic volatility of consumer preferences or economic shifts. Therefore, blockchain is more effective at fixing technical issues upstream than at managing external uncertainty downstream.

Large customers may also resist blockchain. Evidence from a large sample of Chinese firms shows that high customer concentration leads to lower blockchain adoption by suppliers (Ren & Li, 2025). Large customers worry about losing their bargaining power or leaking secrets. This resistance limits the benefits of blockchain in the downstream part of the chain. Even if the technology improves the upstream, these benefits may not reach the downstream.

Hypothesis 3. Blockchain technology has a stronger effect on the stability of upstream suppliers than on downstream customers.

1.8 Environmental Pressure

Digital transformation is not free. Firms often lack the motivation to adopt new technology in stable environments. The value of blockchain as a stabilizer is most clear when external shocks occur and traditional methods fail. Economic value is often tied to the level of demand in the environment.

Recently, global policy uncertainty and trade protectionism have increased risks for cross-border supply chains. In these high-pressure environments, the cost of building trust increases (Hudson, N. E., 2022). Traditional reputation systems often fail during periods of turmoil. Reports from the OECD (2021) suggest that firms face double shocks to both supply and demand. In these situations, blockchain becomes a tool for survival. Its permanent records help with compliance audits. Its smart contracts provide security when trust is low. Its decentralized nature offers a backup when centralized chains break.

In contrast, firms in stable environments do not need to pay for extra supply chain insurance. Traditional management tools are sufficient for daily operations. In such cases, the marginal benefit of blockchain is low. Therefore, environmental uncertainty is a key condition for the value of blockchain. The technology will have a stronger stabilizing effect when external pressure is high.

Hypothesis 4. The effect of blockchain technology on supply chain stability is more significant when environmental uncertainty is high.

1.9 Resource and Capability Thresholds

Not all firms can easily implement blockchain technology. While environmental pressure creates the demand, resources and capabilities determine the supply. A firm needs the right tools to gain the benefits of the technology.

Blockchain deployment is resource-intensive. Setting up nodes and developing smart contracts requires significant capital and technical talent. Furthermore, its effectiveness depends on existing digital infrastructure. Blockchain data must integrate with a firm's production and management systems. Firms with low financial constraints and strong digital foundations can achieve this integration (J. Zhao & Liu, 2024). Without these resources, blockchain may become an expensive tool that does not fit the business. Research shows a large gap between having a budget and actually deploying the technology (Yahaya, 2026). This proves that implementation requires a balance between money, governance, and talent.

Therefore, the impact of blockchain varies based on firm characteristics. Firms with plenty of resources and solid digital bases can fully use the potential of blockchain. Firms with limited resources may fail to see the benefits.

Hypothesis 5. The effect of blockchain on supply chain stability is more significant in firms with strong resources and better digital foundations.

1.10 Technical Synergy between AI and Blockchain

Blockchain handles the execution of contracts and the verification of rights. It provides the infrastructure for trust. Meanwhile, AI and big data handle the prediction of information and the optimization of decisions(Winata, 2022). AI models supply chain data to provide support for inventory and risk management(Baryannis et al., 2019). AI senses and analyzes signals, while blockchain programs those decisions into smart contracts. This creates a complete loop of sensing, deciding, and executing. Empirical studies confirm that this combination improves response speeds and recovery during disruptions (Nguyen et al., 2021).

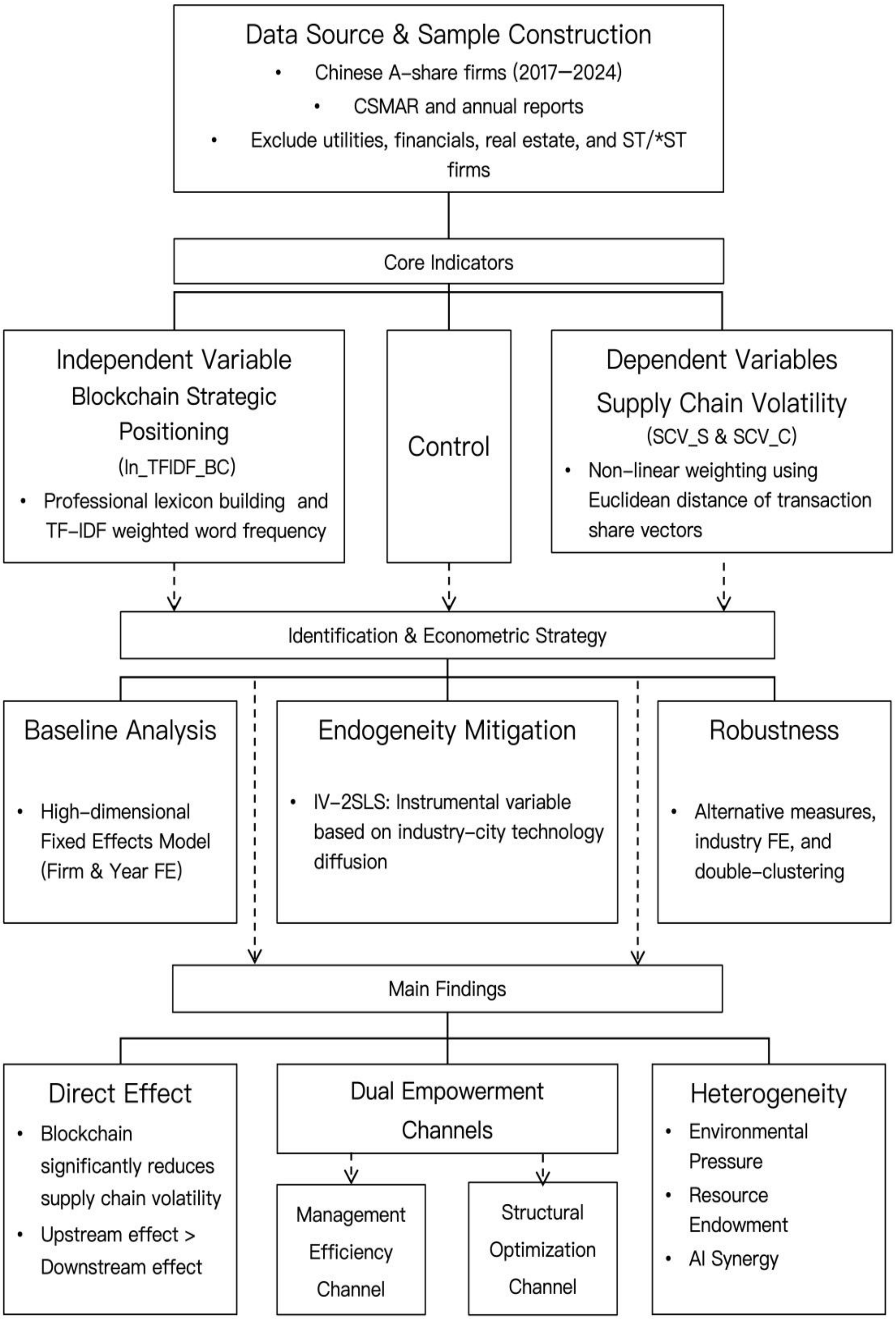
By 2026, the growth of computing power has solved many early efficiency problems of blockchain. This makes the deep integration of AI and blockchain possible. I conclude that using both technologies together will improve supply chain stability more than using either one alone.

Hypothesis 6. Blockchain technology improves supply chain stability more effectively in firms that also use artificial intelligence.

2. Design and data

This section outlines the experimental design, data, and empirical strategy, with the design framework illustrated in Figure 1.

Figure 1. Research Design Framework



2.1 Data Sources and Sample Construction

This study selects A share firms listed on the Shanghai and Shenzhen Stock Exchanges from 2017 to 2024 as the research sample. A share firms refer to firms that are registered in mainland China, whose stocks are priced in RMB, and whose stocks are traded on domestic stock exchanges. The year 2017 is chosen as the starting year of the study because blockchain technology entered a stage of rapid development in China's supply chain management field from that year. At the same time, this period also reflects data availability and statistical completeness, which ensures that the sample can capture the latest developments in blockchain supported supply chain.

Firm financial and supply chain data are drawn primarily from the China Stock Market and Accounting Research database (CSMAR). Blockchain disclosure is measured from the annual reports of listed firms. The instrumental-variable and heterogeneity analyses additionally draw on city-level internet infrastructure data, the China Economic Policy Uncertainty index, firm overseas-revenue data, and city-level coronavirus disease 2019 (COVID-19) confirmed-case data, all obtained from CSMAR and the corresponding public statistical sources.

The initial sample is processed through three screening steps. First, firms in the production and supply of electricity, heat, gas, and water, and firms in the financial and real estate industries, are excluded, because these sectors are largely state-controlled and their supply chain operations often lack independent decision-making. Second, firms under special-treatment status are removed. In the Chinese stock market, the Shanghai and Shenzhen exchanges place a firm under Special Treatment (ST) when it has reported financial abnormalities, most commonly two consecutive years of net losses. When a firm's financial condition further worsens and it faces an actual delisting risk, it is placed on the Delisting Risk Warning list, which is marked as *ST. Both ST and *ST firms are in financial distress, and their supplier and customer relationships are affected by distress rather than normal operating decisions. Therefore, they are excluded from the sample. Similarly, firms that receive non standard audit opinions, including qualified opinions, adverse opinions, or disclaimers of opinion, are also removed. Third, firm year observations with missing values in core variables or control variables are excluded. To prevent extreme values from influencing the results, all continuous variables are winsorized at the 1st and 99th percentiles, meaning that values below the 1% are set equal to the 1st percentile and values above the 99% are set equal to the 99%. After this screening, the final sample is an unbalanced panel of 8,948 firm-year observations.

2.2 Independent Variable: Blockchain Strategic Positioning

2.2.1 The Measurement Challenge and the Limitations of Existing Approaches

A fundamental challenge in evaluating technological empowerment lies in measuring technology adoption itself. As an emerging technology, blockchain is difficult to measure at the firm level through any single financial indicator (Zhu et al., 2026). Previous empirical studies mainly use two methods, but both methods have important limitations. The first method treats blockchain adoption as a binary choice in which firms either use the technology or do not use it (R. Li & Wan, 2021). This method simplifies a gradual strategic process into a single switch and ignores all information about the degree of firm investment. The second method relies on questionnaire surveys of supply chain professionals (Sheel & Nath, 2019), but this method is limited by small sample size, respondent subjectivity, and the lack of a standardized and scalable firm level database. Therefore, this study does not directly observe blockchain implementation. Instead, it uses the intensity of blockchain related strategic disclosure in annual reports as a scalable measure of firms' blockchain strategic orientation.

2.2.2 Theoretical Basis: The Attention-Based View and Signaling Theory

Why can disclosure intensity represent strategic positioning rather than just cheap talk? Based on the theoretical framework, this study proposes two complementary arguments. First, according to the attention based view (Ocasio, 2011; Ocasio et al., 2018), which argues that firm behavior depends on how managers allocate their limited attention, firm level technology upgrading requires managers to make strategic attention allocation. The amount of text devoted to blockchain strategy in annual reports reflects the degree of firm commitment to this technology. Second, according to signaling theory (Connelly et al., 2011; Healy & Palepu, 2001; Spence, 1973), which studies how informed parties credibly transmit unobservable information to uninformed parties through costly and hard to imitate actions, repeated and audited disclosure of blockchain strategy in a highly regulated corporate environment is a costly and verifiable signal of a firm’ s commitment to supply chain transparency (Chod et al., 2019). This ex ante strategic positioning can reduce compliance risk and build mutual trust among supply chain nodes, while mutual trust is a necessary institutional condition for actual technology implementation. Therefore, disclosure intensity reflects the strategic positioning stage in the technology adoption process.

2.2.3 Construction of the TF-IDF Disclosure Index

The independent variable is constructed in four steps, following Xiong et al. (2025) and the broader literature on text-based measurement in the digital economy.

First, a dedicated blockchain technology lexicon is built. The core vocabulary is drawn from the glossary of blockchain terms jointly published by Practical Law and the Loan Syndications and Trading Association (2019), covering fundamental concepts such as distributed ledger, smart contracts, consensus mechanisms, and proof of work.

Second, the annual reports of all A-share listed firms for 2017 – 2024 are collected. The Management Discussion and Analysis (MD&A) sections are extracted using Optical

Character Recognition (OCR) and regular expressions, with tables, charts, and formatting codes removed to reduce noise.

Third, to mitigate stylistic disclosure bias across firms and industries, each blockchain term is weighted using the Term Frequency Inverse Document Frequency (TF-IDF) algorithm. TF-IDF is a standard text-mining weighting scheme that gives a higher weight to a word the more often it appears in one document (term frequency) but a lower weight the more widely it appears across all documents (inverse document frequency). Therefore, it lowers the weight of general terms that are common in most reports and increases the weight of rarer but more informative terms. These terms usually indicate more substantive blockchain discussion (Ferreira, 2021; Osmani et al., 2020). For firm i in year t, the raw blockchain disclosure score is calculated using the following formula:

$$BC\_Score_{i,t} = \sum_{k=1}^{K} \frac{f_{k,i,t}}{N_{i,t}} \times ln\left(\frac{D}{d_k}\right) \tag{1}$$

where

BC_Scorei,t – raw blockchain disclosure score of firm i in year t

K – total number of blockchain terms in the lexicon

k – index of an individual blockchain term, running from 1 to K

fk,i,t – number of times the k-th blockchain term appears in the MD&A section of firm i in year t

Ni,t – total word count of the MD&A section of firm i in year t

D – total number of sample firms

dk – number of firms whose MD&A section contains the k-th blockchain term at least once

Fourth, to reduce skewness and facilitate interpretation, a logarithmic transformation is applied, defining the main independent variable using the following formula:

$$\ln\_TFIDF\_BC_{i,t} = \ln\left(1 + BC\_Score_{i,t}\right) \tag{2}$$

where

ln_TFIDF_BCi,t – main independent variable: the log-transformed blockchain disclosure intensity of firm i in year t

BC_Scorei,t – raw blockchain disclosure score of firm i in year t

A higher value of ln_TFIDF_BCi,t indicates denser, more informative blockchain disclosure, and thus a stronger blockchain strategic positioning.

2.2.4 Construct Validity: Positive Arguments and Boundaries

Does disclosure density constitute a valid proxy for strategic positioning? In the Chinese A-share regulatory context, three arguments support its validity. First, the securities disclosure regulations of the China Securities Regulatory Commission (CSRC), the national regulator of China's securities markets, impose legal liability for materially false or misleading statements in annual reports, so disclosure without underlying strategic commitment would expose managers to regulatory sanction, making fabricated blockchain disclosure costly (Chen et al., 2018; Piotroski & Wong, 2012). Second, prior research establishes a robust positive correlation between MD&A technology mentions and actual research and development (R&D) and capital expenditure in the corresponding domain , validating text-based proxies for strategic technology intent (Andreou et al., 2026; Bellstam et al., 2021). Third, the TF-IDF scheme specifically downweights generic mentions common to all reports and upweights firm-specific, context-rich terms that signal substantive discourse (Loughran & Mcdonald, 2011).

This study also clearly states the boundary of this measure. ln_TFIDF_BC_i,t captures strategic intent and disclosed attention rather than directly measuring blockchain infrastructure that has already been deployed. This is a deliberate design choice and is consistent with the signaling logic discussed above. Disclosure is positively related to deployed capability, but it is not the same as deployed capability. If disclosure overstates actual deployment, the estimated effect is more likely to be weakened toward zero rather than reversed in direction. Future research can address this limitation by combining patent data, smart contract transaction frequency, or survey based capability measures (Osmani et al., 2020).

2.3 Dependent Variable: Supply Chain Volatility as an Inverse Proxy for Resilience

2.3.1 Construction of the SCV Index

Existing studies typically measure supply chain stability through the retention rate of prior-year partners (Ersahin et al., 2023; B. Liu et al., 2022). However, the retention-rate measure neglects significant shifts in transaction shares among retained partners. This method fail to capture the supply network's behavior under stress.

To capture both partner turnover and transaction-share changes simultaneously, this study constructs firm-level dynamic volatility measures for suppliers and customers, denoted Supply Chain Volatility on the supplier side (SCV_S) and on the customer side (SCV_C). Unlike linear methods in which weights increase in proportion to share changes (Zhu et al., 2026), this study uses Euclidean distance, which is the ordinary straight line distance between two points. In this study, it is applied to two vectors of transaction shares. This method gives greater weight to large and sudden changes. Therefore, it can more accurately identify major supply chain restructuring and avoid bias caused by the subjective estimation of missing observations.

For a focal firm i in year t, the set of partners considered is the union of all partners appearing in either year t or year t - 1; when a partner exists in one period but not the other, its missing share is assigned a value of zero, so that complete partner entry or exit is fully accounted for. Supply chain volatility is defined as the Euclidean distance between the two consecutive-year share vectors, calculated using the following formula:

$$SCV_{i,t} = \sqrt{\sum\nolimits_{p \in P} (W_{i,p,t} - W_{i,p,t-1})^2} \tag{3}$$

where

$SCV_{i,t}$ – supply chain volatility of firm i in year t

P – the set of all unique partners (suppliers or customers) appearing in the transaction records of firm i in year t or in year t−1

p – index of an individual partner belonging to the set P

$W_{i,p,t}$ – share of partner p in the total transaction value of firm i in year t (equal to zero if partner p is absent in year t)

$W_{i,p,t-1}$ – share of partner p in the total transaction value of firm i in year t−1 (equal to zero if partner p is absent in year t−1)

The supplier-side measure SCV_S is computed from purchase shares with the firm's suppliers; the customer-side measure SCV_C is constructed under an identical logical framework, replacing supplier purchase shares with customer sales shares. Both SCV_S and SCV_C are non-negative; higher values indicate greater partner turnover and larger transaction-share fluctuations, signifying lower supply chain stability.

One measurement boundary must be stated clearly. CSMAR reports transaction share data only for the top five suppliers and customers of each listed firm. Therefore, the SCV index is constructed from these top five share vectors and captures volatility among a firm's largest relationships. Turnover among smaller and long tail partners cannot be observed. Since large relationships are exactly those whose disruption has the most serious effect, this boundary is unlikely to change the interpretation of the measure. However, it implies that SCV may understate total network volatility.

2.3.2 The Conceptual Bridge: SCV as an Inverse Proxy for Resilience

Supply chain resilience is essentially a dynamic and latent organizational capability. It refers to the capacity to anticipate disruptions, absorb their impact, and recover from them (Ponomarov & Holcomb, 2009; Tukamuhabwa et al., 2015b). A firm cannot be directly asked to report a resilience score. Resilience can only be observed through its behavioral outcomes under stress. At the micro level, it is reflected in a firm’s ability to smooth operational shocks. A resilient supply chain can absorb systemic disturbances and recover quickly, so it shows lower realized volatility. In contrast, a sharp increase in SCV indicates that the network failed to absorb a shock, as partners were lost and transaction shares were greatly reshuffled.This study therefore conceptualizes SCV as an inverse empirical proxy for realized supply chain resilience under continuous market friction, rather than as a passive performance outcome.

SCV index has three properties. First, it captures the intensive margin, which means changes in the size of existing relationships. Two firms may both keep their top five partners, but they may experience very different levels of transaction share reshuffling. Only a dynamic measure can detect this difference. Second, it captures the extensive margin, which means the entry and exit of relationships. When a partner fully exits, a zero share replaces a positive share. The Euclidean weight then reflects the prior importance of the exited partner, so major relationship disruptions are not hidden. Third, the non-linear Euclidean weighting assigns disproportionate weight to large-magnitude changes relative to small fluctuations, which is theoretically appropriate because resilience failures are characterized by discontinuous, high-magnitude disruption rather than smooth variation (Ivanov & Dolgui, 2020b).

2.3.3 Adaptive versus Disruptive Reconfiguration and the Boundary of Interpretation

A potential concern is that not all reconfiguration indicates fragility. During a crisis, a firm may deliberately switch to a more reliable supplier. This switch may itself reflect adaptive resilience rather than a sign of disruption. This concern is addressed on three levels. First, by construction, the Euclidean-distance index assigns disproportionate weight to large, abrupt dislocations and little weight to small, incremental adjustments; since voluntary adaptation typically unfolds gradually whereas involuntary disruption is abrupt and high-magnitude, the index is inherently more sensitive to the latter. Second, the empirical pattern is inconsistent with the interpretation that low SCV reflects rigidity. Blockchain disclosure is associated with lower supply chain concentration. This means that firms maintain stable partner shares within more diversified networks. This pattern is the main feature of adaptive resilience rather than lock in. Were low SCV merely a symptom of organizational rigidity, it would be accompanied by rising concentration rather than the diversification observed.

Third, this study nonetheless acknowledges that the index cannot perfectly separate adaptive from disruptive turnover at the level of an individual partner change. Therefore, SCV is best understood as a measure of the observable structural volatility dimension of resilience, rather than a complete measure of the latent construct itself. Its interpretation as inverse resilience is strongest when volatility reflects sudden, involuntary, and large partner share disruptions. Accordingly, the SCV findings are interpreted jointly with the concentration and heterogeneity evidence, rather than treating the volatility measure as a self-sufficient proxy for resilience.

2.4 Control Variables and Other Variable Definitions

2.4.1 Control Variables and the Rationale for Their Selection

To effectively avoid omitted variable bias, this study carefully selects control variables from four core dimensions. These variables jointly and endogenously affect firms' blockchain strategic positioning and supply chain volatility. Financial and operating conditions, including Return on Assets (ROA), leverage, and growth rate, determine the financial base for firms' strategic technology investment and the risk exposure related to daily expansion. Firm basic characteristics, including size and age, reflect the economies of scale that support new technology implementation and the historical buffering capacity of supply chain networks. Corporate governance structure, including ownership concentration and board structure, captures the strategic vision that drives long term technology investment and the internal risk control level that reduces risk. The institutional environment, measured by state ownership, accurately captures the policy driven motive for digital transformation in the Chinese context and the implicit supply chain stability guarantee that is specific to the state system.

Return on Assets (ROA), defined as net profit divided by total assets, captures profitability: more profitable firms have greater internal resources to fund technology-related initiatives and may also sustain more stable supplier and customer relationships. Financial leverage (Lev), defined as total liabilities divided by total assets, reflects a firm's debt burden and risk tolerance: highly leveraged firms face tighter financial constraints that affect both their willingness to invest in new technology and the stability of their trading relationships. Revenue growth (Growth), defined as the year-on-year growth rate of operating revenue, controls for a firm's expansion stage: rapidly growing firms naturally reconfigure their partner base more frequently and may also differ systematically in disclosure behavior. Ownership concentration (Top1), defined as the shareholding percentage of the largest shareholder, captures corporate-governance structure: concentrated ownership shapes strategic decision-making, including both technology-disclosure choices and supply chain management. State-Owned Enterprise status (SOE), a binary indicator equal to one for firms ultimately controlled by the state and zero otherwise, controls for ownership type: state-owned and non-state-owned firms differ in strategic autonomy, access to resources, and exposure to administrative guidance. Controlling for these five variables, together with firm and year fixed effects, mitigates omitted-variable bias arising from observable firm heterogeneity.

2.4.2 Mediating and Heterogeneity Variables

Beyond the baseline controls, the study employs two further sets of variables.

The mediating variables are used in the channel analysis. The managerial efficiency channel is measured by the administrative expense ratio (Admin_Exp_Ratio), defined as administrative expenses divided by operating revenue. The structural optimization channel is measured by supply chain concentration (SC_Concentration). In the empirical analysis, SC_Concentration is log-transformed, therefore the descriptive statistics may take negative values. Supplier concentration is measured as the proportion of total procurement value accounted for by the firm’s top five suppliers, while customer concentration is measured as the proportion of total sales revenue accounted for by the firm’s top five customers. A lower value of supply chain concentration indicates a more diversified supply chain structure. This means that the firm spreads its transactions across a broader set of partners rather than relying heavily on a few partners. Because diversification can reduce the impact of disruption from any single partner, a decrease in concentration is interpreted as structural optimization.

The heterogeneity variables define the subsamples used in the boundary-condition analysis. Economic Policy Uncertainty (EPU) is the annual mean of the China Economic Policy Uncertainty index, an index measuring the degree of uncertainty in government economic policy; high-EPU years are identified by a split at the sample median. Foreign business orientation (Is_Foreign_Oriented) is a binary indicator equal to one for firms with positive overseas operating revenue. Industry concentration is measured by the Herfindahl-Hirschman Index (HHI), a standard measure of market concentration equal to the sum of the squared market shares of all firms in an industry, where a higher value indicates a more concentrated, less competitive market. Following the OECD approach (2021), the HHI is calculated from firm operating revenue within each industry year cell. Industry year groups with fewer than five firms are treated as missing to ensure reliability. The indicator HHI_Low equals one when the industry year HHI is below the median, which represents a more competitive market. Financing constraint (FC_High) is a binary indicator equal to one for firms with below-median scaled free cash flow; digital foundation (Dig_High) equals one for firms with above-median digital infrastructure; and Artificial Intelligence integration (AI_High) equals one for firms with above-median use of artificial intelligence.

In conclusion, all variables, their symbols, and their definitions are summarized in Appendix A.

3. Empirical Strategy

This chapter sets out the empirical strategy used to test the hypotheses developed in Chapter 1. The identification strategy combines two complementary approaches. The main approach is a two way fixed effects panel regression. This method uses within firm variation over time to estimate the relationship between blockchain strategic disclosure and supply chain volatility in Section 3.1. The supporting approach is a Two Stage Least Squares estimation using an instrumental variable. This method addresses potential endogeneity and provides bounded causal evidence in Section 3.2. Building on these, Section 3.3 specifies the transmission-channel tests, Section 3.4 the heterogeneity tests.

3.1 Baseline Model: Two-Way Fixed Effects

The baseline analysis uses a two way fixed effects model. This is a panel regression model that removes firm specific differences and year specific differences at the same time. It is used to examine the relationship between blockchain disclosure intensity and supply chain volatility. The model is specified as follows:

$$SCV_{i,t} = \alpha + \beta \ln\_TFIDF\_BC_{i,t} + \gamma Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

where

$SCV_{i,t}$ – supply chain volatility of firm i in year t; estimated separately as supplier-side volatility (SCV_S) and customer-side volatility (SCV_C)

$ln\_TFIDF\_BC_{i,t}$ – main independent variable: the log-transformed blockchain disclosure intensity of firm i in year t

$Controls_{i,t}$ – vector of time-varying firm-level control variables for firm i in year t: Return on Assets (ROA), financial leverage (Lev), revenue growth (Growth), ownership concentration (Top1), and State-Owned Enterprise status (SOE)

μ_i – firm fixed effect, capturing all time-invariant unobserved characteristics of firm i (for example, its corporate culture or location)

λ_t – year fixed effect, capturing macroeconomic shocks common to all firms in year t (for example, a nationwide economic downturn)

α – constant term

β – coefficient of interest, measuring the association between blockchain disclosure intensity and supply chain volatility

γ – vector of coefficients on the control variables

$\varepsilon_{i,t}$ – error term and

3.2 Identification Strategy: Instrumental Variable and Weak-Instrument Diagnostics

3.2.1 Sources of Endogeneity

The baseline coefficient β cannot be interpreted as causal without further assumptions because ln_TFIDF_BC_i,t may be endogenous for two reasons. The first reason is reverse causality. Firms that already face high supply chain volatility may be more or less likely to disclose a blockchain strategy. Therefore, causality may run from volatility to disclosure rather than from disclosure to volatility. The second reason is omitted variable bias. An unobserved factor, such as overall managerial quality, may increase blockchain disclosure and reduce volatility at the same time, which can produce a false negative relationship. To address both concerns, this study uses an instrumental variable strategy estimated by Two Stage Least Squares (2SLS).

3.2.2 Construction of the Instrumental Variable

A valid instrument must be correlated with the endogenous regressor but affect the dependent variable only through that regressor. The instrument used here is an interaction of two components.

The first component is the leave-one-out peer disclosure level (IV_Peer): for each firm, the average ln_TFIDF_BC of all other firms in the same city and the same industry in the same year. It is calculated using the following formula:

$$IV\_Peer_{i,t} = \frac{\ln TFIDF - BC_{j,t} - \ln\_\ TFIDF\_\ BC_{i,t}}{N_{i,t} - 1} \quad 5)$$

where

IV_Peeri,t – leave-one-out average blockchain disclosure intensity of the industry-city peer group of firm i in year t

Gi,t – the peer group of firm i: all firms located in the same city and belonging to the same industry as firm i in year t

j – index of an individual peer firm belonging to the group Gi,t

ln_TFIDF_BCj,t – blockchain disclosure intensity of peer firm j in year t

ln_TFIDF_BCi,t – blockchain disclosure intensity of the focal firm i itself, subtracted so that the firm's own value is excluded

Ni,t – number of firms in the peer group Gi,t

The second component is local broadband infrastructure, measured by the natural logarithm of the number of regional broadband access ports (ln_BroadBandSubPort). The instrument is the interaction of the two:

$$IV\_Interact_{i,t} = IV\_Peer_{i,t} \times ln\_\ BroadBandSubPort_{c,t} \quad 6)$$

where

IV_Interacti,t – the instrumental variable for firm i in year t

IV_Peeri,t – leave-one-out peer disclosure level

ln_BroadBandSubPortc,t – the natural logarithm of one plus the number of broadband access ports in city c, which is the city where firm i is located, in year t

The economic rationale is that a firm's propensity to adopt blockchain is shaped by the demonstration effect of regional industry peers and by the cost-reducing capacity of local telecommunications infrastructure, whereas an individual firm's idiosyncratic supply chain volatility is unlikely to drive city-level infrastructure development or aggregate peer behavior.

3.2.3 The 2SLS Specification

To ensure the statistical validity of this strategy, the identification framework incorporates cluster-robust effective F-statistics to diagnose weak instrument vulnerabilities and supplements conventional Wald-type inferences with the weak-instrument-robust Anderson-Rubin Wald test. Furthermore, to safeguard the exclusion restriction against the confounding influence of alternative digital channels such as enterprise resource planning or e-commerce platforms, the baseline specification is Augmented with a comprehensive corporate digital transformation index, thereby isolating the localized average treatment effect of blockchain adoption driven strictly by peer-group dynamics and regional digital infrastructure.

A specification difference between the baseline and the IV estimation must be made explicit. The baseline two-way fixed-effects model absorbs firm fixed effects, whereas the 2SLS specification replaces firm fixed effects with industry and city fixed effects, because the instrument's identifying variation operates at the industry-city-year level and is partially collinear with firm fixed effects. A direct consequence is that the IV and baseline coefficients are not estimates of the identical parameter: the IV estimate is not purged of time-invariant firm heterogeneity in the same way the baseline is. The IV results should therefore be read as a complementary identification exercise that addresses peer- and infrastructure-driven variation in disclosure, rather than as a strict causal replacement for the baseline coefficient. This limitation is revisited in the concluding chapter.

3.3 Transmission Channel Test Design

This section presents the tests for the two possible channels through which blockchain disclosure may be related to lower volatility, as stated in Hypotheses H2a and H2b. The managerial efficiency channel in H2a is measured by the administrative expense ratio (Admin_Exp_Ratio), which is defined as administrative expenses divided by operating revenue. The structural optimization channel in H2b is measured by supply chain concentration (SC_Concentration).

The indirect effect through each channel is estimated by using a nonparametric bootstrap with 5,000 replications. This resampling method repeatedly draws samples from the data to build an empirical distribution of the indirect effect. Percentile confidence intervals are then calculated from this distribution. A contrast test is used to compare the absolute sizes of the two channels. This study also clearly states the methodological boundary of the channel analysis. In an observational fixed effects panel, the mediators are endogenous outcomes themselves. Therefore, the estimates should be understood as a descriptive decomposition of the two channels, rather than as a formally identified causal mediation analysis. The results are interpreted in this way throughout Chapter 6.

3.4 Heterogeneity Test Design

This section specifies the tests of the boundary conditions, as stated in Hypotheses H4 to H6, and these tests are organized according to the Pressure Capability Match framework.

The sample is split, at the median, along six dimensions, and the baseline model is re-estimated within each subsample: Economic Policy Uncertainty (EPU), foreign business orientation, industry concentration (HHI), financing constraint, digital foundation, and Artificial Intelligence (AI) integration. Comparing the coefficient on ln_TFIDF_BC across paired subsamples reveals how the association varies with each dimension.

4. Descriptive Analysis

This chapter provides a preliminary basis for the formal hypothesis testing conducted in Chapter 5 to Chapter 7.

4.1 Descriptive Statistics

Table 1 reports the descriptive statistics of the main variables from 2017 to 2024 sample period.

Table 1 Descriptive Statistics

Variables	N	Mean	SD	Min	P25	Median	P75	Max
SCV_S	8,948	0.1646	0.2231	0.0000	0.0358	0.0900	0.1946	2.0000
SCV_C	8,948	0.1508	0.2400	0.0000	0.0260	0.0704	0.1663	2.2754
SC_Concentration	8,948	-0.6972	0.6656	-5.1850	-1.0906	-0.6094	-0.2083	0.6899
ln_TFIDF_BC	8,948	0.0153	0.2004	0.0000	0.0000	0.0000	0.0000	3.6019
ROA	8,948	0.0311	0.0759	-0.3549	0.0103	0.0366	0.0683	0.2112
Lev	8,948	0.3954	0.2026	0.0547	0.2332	0.3770	0.5375	0.9412
Growth	8,948	0.3286	0.7225	-0.7233	-0.0323	0.1362	0.4313	3.8930
Top1	8,948	32.0648	14.3663	8.2300	21.0300	29.8550	40.6600	74.0200
SOE	8,948	0.2987	0.4577	0.0000	0.0000	0.0000	1.0000	1.0000

Note. The sample comprises 8,948 firm-year observations of Chinese A-share listed firms over 2017-2024. Statistics are computed on the unified estimation sample used in the baseline regressions (firm-year observations with non-missing values on all baseline-model variables, with single-observation firms removed). N denotes the number of observations; SD denotes the standard deviation; All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions follow the construction described in the text.

Three features of the distribution are important. First, blockchain strategic disclosure is highly right-skewed. The mean of ln_TFIDF_BC is only 0.0153, while the 25th percentile, the median, and the 75th percentile are all zero; the maximum is 3.6019. In other words, more than three-quarters of firm-year observations contain no substantive blockchain disclosure at all, and the entire informative variation is concentrated in a minority of firm-years. This pattern is consistent with the nature of an emerging technology whose strategic adoption remains uneven across the corporate population. It has a direct consequence for interpretation: the identifying variation in the empirical models, and therefore the Local Average Treatment Effect recovered by the instrumental-variable estimation in Chapter 5, derives specifically from this disclosing subset of firms rather than from the average firm in the economy.

Second, supplier-side volatility is, on average, higher than customer-side volatility. The mean of SCV_S (0.1646) exceeds the mean of SCV_C (0.1508), and the same ordering holds at the median (0.0900 versus 0.0704). This is the first model free indication that upstream procurement relationships are structurally less stable than downstream sales relationships. This pattern serves as the basis for the directional asymmetry prediction in Hypothesis 3 and is discussed in greater detail in Section 4.3. Both volatility measures have a lower bound of zero and display a right skewed distribution where the means are higher than the medians. Furthermore both maximum values are greater than 2.0. This indicates that a considerable number of companies experience a nearly complete restructuring of their top five partner portfolios within a single year.

Third, the control variables display values typical of the population of Chinese A-share listed firms: average return on assets is 3.1%, average leverage is 39.5%, average revenue growth is 32.9% with a large standard deviation of 0.72, the largest shareholder holds 32.1% of shares on average, and 29.9% of firm-year observations correspond to state-owned enterprises.

4.2 Correlation Analysis and Multicollinearity Diagnostics

Table 2 reports the pairwise correlation matrix of the main variables, with Pearson correlations below the diagonal and Spearman rank correlations above it.

Table 2 Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) SCV_S	1.000	0.358***	0.003	-0.022**	-0.116***	0.061***	-0.087***
(2) SCV_C	0.561***	1.000	0.012	-0.071***	-0.049***	0.106***	-0.115***
(3) ln_TFIDF_BC	0.005	0.003	1.000	-0.006	-0.007	0.055***	-0.033***
(4) ROA	0.035***	-0.001	0.004	1.000	-0.376***	-0.055***	0.208***
(5) Lev	-0.133***	-0.087***	-0.007	-0.350***	1.000	-0.040***	-0.056***
(6) Growth	0.091***	0.133***	0.110***	-0.026**	-0.044***	1.000	-0.038***
(7) Top1	-0.050***	-0.046***	-0.029***	0.202***	-0.045***	-0.029***	1.000
(8) SOE	-0.107***	-0.099***	-0.000	-0.042***	0.243***	0.037***	0.239***

*Note. The table reports pairwise correlations among the main variables (N = 8,948). Pearson correlation coefficients are reported below the diagonal and Spearman rank correlation coefficients above the diagonal. Variables are numbered (1)-(8) as listed in the first column. *** , ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.*

The most important observation in Table 2 involves the relationship between blockchain information disclosure and supply chain volatility. The correlation coefficient between ln_TFIDF_BC and SCV_S is 0.005 and the unconditional correlation coefficient between ln_TFIDF_BC and SCV_C is 0.003. Neither of these values is statistically significant. The corresponding Spearman correlation coefficients which are 0.003 and 0.012 respectively are also not statistically significant. In other words at the raw cross sectional comovement level there is no detectable association between blockchain information disclosure and supply chain volatility.

This finding does not weaken the thesis; rather, it clarifies why the empirical strategy of Chapter 3 is necessary, and it should be read together with two further facts. First, blockchain disclosure is, as Section 4.1 showed, extremely right-skewed, with most firm-years equal to zero; a simple correlation coefficient is a poor summary of the relationship for such a variable. Second, companies that disclose blockchain strategies and those that do not exhibit systematic differences in size, growth, governance, and digital maturity. These differences themselves are correlated with supply chain volatility in opposite directions. Therefore a cross sectional correlation analysis confounds the within firm relationship of interest with numerous confounding factors across companies. This ultimately yields an estimate that is close to zero. The hypothesized stabilization relationship is essentially a within firm effect. It focuses on how volatility changes as a firm increases its blockchain strategy disclosure. Such an effect can only be isolated once firm fixed effects absorb time-invariant between-firm heterogeneity and year fixed effects absorb common shocks. Therefore, the raw correlation that is close to zero is precisely the empirical motivation for the two way fixed effects design. It also specifically demonstrates that a simple cross sectional study would incorrectly conclude that blockchain has no effect.

There are two other notable features in the matrix. The two volatility measures show a significant positive correlation with a Pearson correlation coefficient of 0.561. This confirms that supplier side volatility and customer side volatility often have a synergistic effect. However they remain independent and deserve separate analysis..

Finally, Table 3 reports variance inflation factors (VIF) for the baseline specification, computed both on the raw variables (pooled OLS) and after the within-transformation by firm and year that matches the identifying variation of the baseline model.

Table 3 Variance Inflation Factor (VIF) Diagnostics

Variables	VIF (Pooled OLS)	VIF (Two-way FE)	1/VIF (FE)
ln_TFIDF_BC	1.013	1.001	0.999
ROA	1.189	1.094	0.914
Lev	1.219	1.083	0.923
Growth	1.020	1.008	0.992
Top1	1.118	1.008	0.992
SOE	1.143	1.005	0.995
Mean VIF	**1.117**	**1.033**	

Note. The table reports variance inflation factors (VIF) for the baseline specification (the core regressor and the control variables; N = 8,948). The column 'Pooled OLS' is computed on the raw variables; the column 'Two-way FE' is computed after the within-transformation by firm and year, matching the identifying variation of the baseline model. A common rule of thumb flags potential multicollinearity when the VIF exceeds 10; all values reported here are well below this threshold.

All variance inflation factors lie between 1.0 and 1.22, with a mean of 1.033, far below the conventional threshold of 10; the values fall further once the within-transformation is applied. Multicollinearity is therefore not a concern. This diagnostic is crucial for explaining the raw correlation that is close to zero discussed above. It confirms that the independent variables are not highly correlated with each other. Therefore the lack of an unconditional correlation between information disclosure and volatility is not a statistical artifact caused by multicollinearity. Instead it truly reflects cross sectional confounding. The fixed effects model is designed precisely to eliminate this confounding.

The descriptive evidence presented in this chapter systematically builds the empirical framework for the subsequent formal analysis. However limited by simple descriptive statistics this evidence is not sufficient to conduct rigorous causal inference for the research hypotheses. Nevertheless the existing data show the feasibility and potential for further research. First blockchain strategy disclosure has achieved considerable prevalence among sample firms and exhibits significant variation over time within different companies. This lays the data foundation for implementing a within firm research design. Second supply chain volatility not only demonstrates the upstream and downstream asymmetry predicted by

Hypothesis 3 but also shows significant stress event characteristics during specific periods such as the pandemic. Additionally all core variables possess good statistical properties. Crucially the unconditional correlation between disclosure intensity and volatility in the cross section is close to zero. This indicates that the potential relationship between the two is masked by firm level heterogeneity and time trends and cannot be captured through a simple correlation analysis. Only by controlling for firm and year fixed effects and stripping away the influence of these confounding factors can the true internal connection between the two be revealed. In response to these challenges Chapter 5 will introduce the two way fixed effects model and instrumental variable strategy established in Chapter 3. This aims to accurately isolate the net within firm effect between blockchain strategic positioning and supply chain volatility.

5. Finding 1: Blockchain Strategic Positioning and Supply Chain Volatility

This chapter connects these two bridges through empirical research. It links the measurement side of the chain with the outcome side by investigating whether a stronger blockchain strategic positioning is systematically associated with lower supply chain volatility in Hypothesis 1. It also investigates whether this correlation is stronger on the upstream supplier side than on the downstream customer side in Hypothesis 3. This chapter sequentially works through three nested identification layers, including the baseline high dimensional fixed effects estimation, a series of robustness tests and the weak instrument robust instrumental variable two stage least squares analysis

The logical argument of this chapter is based on two core interpretive commitments. These commitments serve as the foundation for the reasoning throughout the entire chapter rather than an afterthought to the research findings. Therefore they are explicitly defined at the beginning.

First because the core independent variable in the regression model measures the strategic positioning of a firm rather than its actual deployment capability the resulting coefficients must be strictly interpreted as the effect of strategic positioning instead of the utility of fully implemented technology. Based on signaling theory there is a monotonic positive relationship between strategic positioning and actual deployment. If there is exaggerated information disclosure known as greenwashing it might attenuate the absolute value of the estimated coefficient to a certain extent but it will not alter its directional sign.

Second because the supply chain volatility indicator constructed in this research is essentially a reverse proxy variable a negative coefficient in the regression results should be interpreted as being consistent with a trend of enhanced supply chain resilience. It cannot be directly equated to a physical measure of resilience itself.

5.1 Baseline Regression

The baseline specification regresses supplier-side volatilityand customer-side volatility on blockchain strategic disclosure intensity, a vector of firm-level controls, and firm and year fixed effects. The two-way fixed-effects structure absorbs all time-invariant firm heterogeneity and all common annual shocks, so that identification rests on within-firm changes in strategic positioning over time. Table 4 reports the results.

Table 4 Blockchain Disclosure Intensity and Supply Chain Volatility: Baseline Estimates

Variables	(1) SCV_S	(2) SCV_C
ln_TFIDF_BC	-0.0411***	-0.0320**
	(-3.310)	(-2.563)
ROA	0.1609***	0.1357**
	(3.208)	(2.321)
Lev	-0.1037**	-0.0984**
	(-2.472)	(-2.090)
Growth	0.0132**	0.0133*
	(2.185)	(1.806)
Top1	-0.0008	-0.0012*
	(-1.273)	(-1.714)
SOE	0.0585**	0.0201
	(2.577)	(0.897)
Observations	8,948	8,948
R-squared	0.3228	0.3149
Firm FE	Yes	Yes
Year FE	Yes	Yes

*Notes. t-statistics in parentheses, based on standard errors clustered at the firm level. SCV_S and SCV_C are supplier- and customer-side supply chain volatility. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

The baseline fixed effects regression results indicate that the intensity of corporate blockchain strategy disclosure has a significant negative effect on supply chain volatility across both upstream and downstream channels. Specifically in column (1) for the supplier side volatility model the estimated coefficient of the core independent variable is -0.0411 and it is statistically significant at the 1% level with a t statistic of -3.31. In column (2) for the customer side volatility model the estimated coefficient is -0.0320 and it is statistically significant at the 5% level with a t statistic of -2.56. Two features of Table 4 already foreshadow the asymmetry analysis. The supplier-side coefficient exceeds the customer-side coefficient in absolute magnitude, and it is estimated more precisely. This regression analysis is based on 8948 firm year observations. The R squared of the supplier model is 0.3228 which indicates that the high dimensional fixed effects structure and control variables effectively explain most of the within firm variation in volatility. From the perspective of economic logic these empirical findings show that firms that engage in more blockchain strategy disclosure through costly and audited channels experience a subsequent reduction in the dynamic deviation of their partner transaction structures. This pattern is consistent with the theoretical definition of resilience established in Chapter 3.

According to the dynamic capability theory the strategic positioning of blockchain by a firm is not a simple repair of the supply chain. Instead it is a progressive logical chain. First the firm reduces compliance risks and establishes institutional trust among various nodes in the supply chain by demonstrating a credible commitment to transparency. This trust is the institutional prerequisite for achieving traceability and automated contract execution. Once this prerequisite is met partners can coordinate raw material flows and delivery schedules based on a shared information baseline. This effectively curbs the tendency of small fluctuations to be amplified progressively through the bullwhip effect. Ultimately this series of transmission mechanisms will effectively reduce the actual deviation of transaction shares. It is important to note that in the impact channels mentioned above the suppression of the bullwhip effect by blockchain theoretically manifests as a negative relationship and this negative sign is theoretically reasonable. This interpretation also resonates with the broader literature. For instance Bennett et al. (2024) define blockchain as the foundational technology that supports secure and transparent transaction records. Furthermore Saberi et al. (2019) emphasize the critical role of blockchain in enhancing supply chain traceability and accountability.

However the preceding analysis currently only characterizes the correlation within the firm. Although these correlations are consistent with the hypothesized direction of the effect firm level fixed effects cannot rule out the interference of time varying confounding factors or reverse causality. For example a company that expects its partner base to become more stable might choose to invest in blockchain information disclosure for this exact reason.

Therefore what the baseline model confirms is the existence of Hypothesis 1 as a robust correlation. Thus, the causal implications behind this correlation will be further explored in Section 5.2.

5.2 Endogeneity and Weak-Instrument-Robust Inference

To address potential endogeneity concerns arising from reverse causality and omitted variables, we employ a two-stage least squares （2SLS） approach. Specifically, we instrument firms' blockchain disclosure intensity using the interaction between leave-one-out industry-city peer adoption and local broadband infrastructure. The first-stage results reported in Table 5 support the relevance of the instrument. The interaction term is negatively and significantly associated with ln_TFIDF_BC （coefficient = −0.0352, $p < 0.001$）. To further evaluate weak-instrument concerns, we report the Montiel-Olea and Pflueger (2013) effective F-statistic. The effective F-statistic is 13.89, exceeding commonly used critical values, which suggests that weak instruments are unlikely to drive the results.

Table 5 Instrumental-Variable (2SLS) Estimates of Blockchain Disclosure on Supply Chain Volatility

Variables	(1) SCV_S Base	(2) SCV_S +Digital	(3) SCV_C Base	(4) SCV_C +Digital
ln_TFIDF_BC	-0.3412**	-0.3430**	0.0825	0.0757
	(0.1444)	(0.1425)	(0.1750)	(0.1693)
ROA	0.0333	0.0339	-0.0943*	-0.0922*
	(0.0546)	(0.0546)	(0.0500)	(0.0501)
Lev	-0.1272***	-0.1266***	-0.1079***	-0.1059***
	(0.0181)	(0.0180)	(0.0234)	(0.0234)
Growth	0.0297***	0.0298***	0.0346***	0.0351***
	(0.0066)	(0.0064)	(0.0069)	(0.0068)
Top1	-0.0004*	-0.0004*	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
SOE	-0.0490***	-0.0490***	-0.0511***	-0.0512***
	(0.0092)	(0.0092)	(0.0098)	(0.0098)
lnDigital		-0.0009		-0.0033
		(0.0028)		(0.0027)
Industry FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8,945	8,945	8,945	8,945
First-stage F	11.07	11.42	11.07	11.42
Effective F	13.89	—	13.89	—
AR test p-value	0.019	—	0.610	—
AR 95% CI	[-0.733, -0.067]	—	[-0.201, 0.631]	—

*Notes. Standard errors in parentheses. The instrument is the interaction between the leave-one-out industry-city peer adoption rate and the natural logarithm of local broadband access ports. Effective F is the Montiel-Olea and Pflueger (2013)statistic; AR denotes the weak-instrument-robust Anderson-Rubin test. * p < 0.10, ** p < 0.05, *** p < 0.01.*

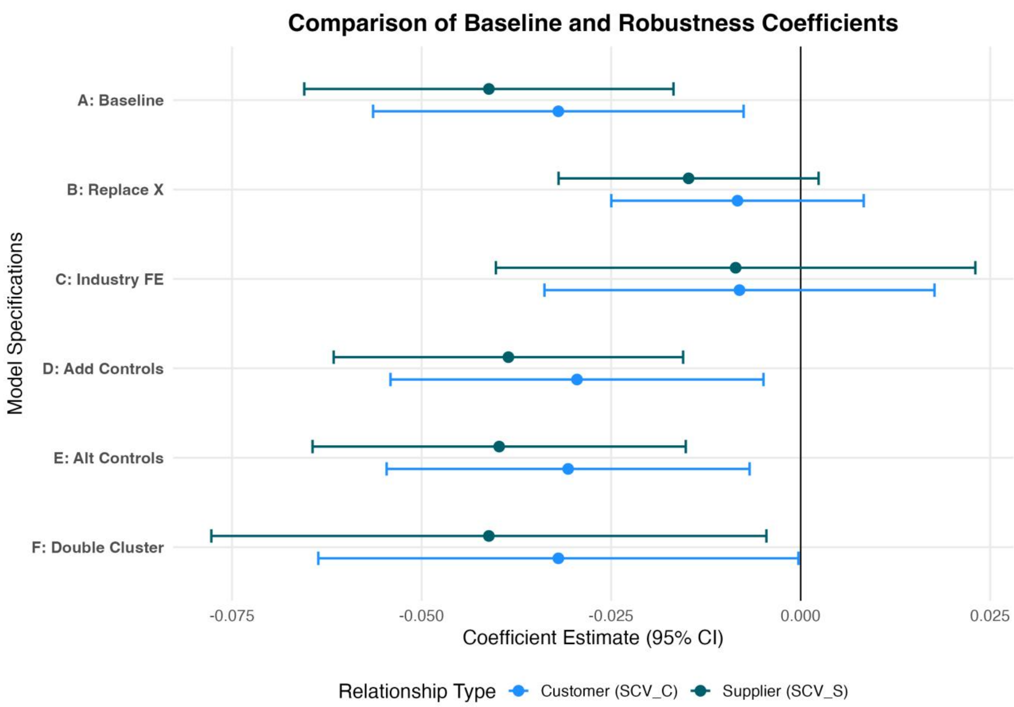
For supplier-side volatility, the second-stage estimate of ln_TFIDF_BC is negative and statistically significant. In column(1), the coefficient is −0.3412 and significant at the 5% level. Since the conventional first-stage F-statistic (F = 11.07)is only moderately above the traditional rule-of-thumb threshold, we additionally rely on the weak-instrument-robust Anderson − Rubin (AR)test for inference. The AR test rejects the null of no effect for supplier-side volatility（AR F = 5.50, p = 0.019）, and the corresponding 95% confidence interval, [−0.733, −0.067], is bounded away from zero and entirely negative. These results indicate that the estimated negative effect of blockchain disclosure on supplier-side volatility remains robust even under weak-instrument-robust inference. The coefficient is also virtually unchanged after controlling for regional digitalization, suggesting that the result is not simply capturing broader differences in local digital infrastructure.

For the customer side the situation is deliberately kept open. The two stage least squares estimate is not statistically significant and its sign is opposite to the baseline fixed effects coefficient in Column 3. The AR test fails to reject the null hypothesis. The AR F value is 0.26 and the p value is 0.610. The associated confidence interval is [-0.201, 0.631]. This interval is wide and spans zero. Therefore this study makes no causal claim about the customer side. The customer side relationship is not causally identified under this strategy. It is reported only as a within firm association from Table 4.

5.3 Robustness Tests

To verify the reliability of the baseline regression, I conduct a series of robustness checks, reported across different panels of Figure 2 and Appendix B.

Figure 2. Comparison of Baseline and Robustness Coefficients



Notes. Points represent estimated coefficients, horizontal lines represent 95% confidence intervals. Standard errors are clustered as specified in each regression panel.

First, to ensure the result is not driven by the construction of the disclosure index, the TF-IDF – weighted measure is replaced with a simple word-count index (ln_BC_WordSum). The coefficient on supplier-side volatility remains negative at − 0.0148 (t = − 1.69), significant at the 10% level. Although the significance is slightly lower than the main specification, the direction of the effect remains consistent. This provides confidence that the stabilizing effect of blockchain is a robust phenomenon regardless of the linguistic measurement technique employed.

Second, to absorb sector-wide shifts toward digitalization, firm fixed effects are replaced with industry fixed effects.The coefficients for ln_TFIDF_BC remain negative. Although the estimate becomes less precise, this result is still reasonable, since the industry fixed effects estimator can no longer account for persistent firm-level heterogeneity. The continued negative sign suggests that the association reflects firm-specific strategic positioning rather than an industry-wide trend toward digital transformation.

Third, additional firm characteristics that could jointly drive positioning and stability are introduced the same as other research (M. Wang & Yang, 2022).This can effectively reduce omitted variable bias. Specifically larger firms usually have more resources and stronger information processing capabilities. They possess more comprehensive supply chain management systems. Therefore, from a resource-based perspective (Barney, 1991), they are more likely to adopt digital technologies such as blockchain and maintain lower supply chain volatility through better resource allocation and risk management (Damanpour, 1992). At the same time firm age reflects the operating experience and long term cooperative relationships of a firm. Older firms might have established more stable supplier networks (Verhoef et al., 2021). Their technology adoption decisions might also differ from those of younger firms. Therefore incorporating firm size and firm age into the model can test whether the negative relationship between blockchain adoption and supplier side volatility is merely driven by firm size advantages or life cycle differences. The empirical results show that after controlling for these two variables the core estimated coefficient remains significantly negative. This indicates that the relationship possesses good robustness.

Fourth, to address correlated errors within firms and within years, standard errors are two-way clustered by firm and year. The point estimate is unchanged at -0.0411; the t-statistic falls to -2.22 but remains significant at the 5% level, confirming robustness to serial correlation and cross-sectional dependence.

Taken together, the baseline regression, endogeneity treatments, and multiple robustness tests confirm that increased blockchain adoption intensity significantly reduces firms' supply chain volatility and enhances supply chain stability. Research Hypothesis H1 is thus supported.

5.4 Directional Asymmetry: Supplier-Side versus Customer-Side

Hypothesis H3 is that the effect of blockchain strategic positioning is stronger upstream than downstream. In the baseline, the supplier-side coefficient (-0.0411, $p < 0.01$) exceeds the customer-side coefficient (-0.0320, $p < 0.05$) in absolute magnitude and the ordering is preserved across every robustness specification. In the IV analysis the asymmetry is sharper still: the supplier side yields a bounded, below-zero AR interval, whereas the customer side is not causally identified at all. H3 is therefore supported, and supported more decisively under the stricter identification standard than under the baseline.

The asymmetry between the supplier side and the customer side can be explained within the theoretical framework of the dynamic capabilities view. Blockchain technology, as a capability, can help firms sense the market, seize opportunities, and adjust processes (Quayson et al., 2023). However, the effect of this capability depends on the stability of market demand (Teece et al., 1997). The problems faced by upstream suppliers are mostly specific management frictions, such as unconfirmed material quality, inaccurate delivery time, and delayed payment. For these upstream problems, blockchain can provide relatively quick solutions through traceability and standardized smart contracts (Cole et al., 2019b; Kshetri, 2018; Yavaprabhas et al., 2023). However, on the downstream customer side, the problems are not standardized management problems. They are more related to random and diverse changes in preferences and demand (Croson & Donohue, 2006; Lee et al., 1997). In the face of such complex changes, blockchain, as a distributed ledger, cannot predict and encode them well. Therefore, to address this problem, the following section introduces artificial intelligence, a technology that can flexibly identify changing customer demand, and examines its joint role with blockchain. In addition, when buyers with strong bargaining power exist in the market, they may block blockchain adoption in order to protect their information advantage and avoid losing bargaining power (C. Li et al., 2025).

Overall, this study provides the first part of the answer to the core question of how strategic positioning is transformed into micro level resilience. It shows that this transformation does exist and that it is mainly concentrated in the upstream segment, where trust and compliance mechanisms can play a role. The specific transmission channels and boundary conditions will be discussed in the following chapters.

6. Finding 2: The Transmission Channels

Chapter 5 showed that a stronger strategic positioning is robustly associated with a lower supply chain volatility (SCV).

However, no matter how robust the average association is, it can answer only half of the question raised in this thesis. The research question is not whether strategic positioning changes together with resilience, but how strategic positioning is translated into resilience. The term translation is the core analytical focus of this study. In this sense, the average effect is like a black box. For managers, it shows that a strategic commitment to blockchain is important, but it does not indicate which part of the firm generates stabilizing value. As a result, it cannot guide where organizations should concentrate their efforts. For the theoretical chain, it leaves a missing middle link. Link 2 argues that strategic positioning first works by reducing compliance risk and building inter-node trust, thereby creating the institutional conditions needed for actual technology implementation. This argument was discussed in Chapter 1, but it has not yet been supported by empirical evidence.

Finding 2 addresses the task of Hypothesis 2 (H2), which holds that the strategic positioning and SCV association is transmitted through two candidate channels: a reduction in managerial friction and a reduction in supply chain concentration.

I need to mention a specific limitation about the concentration channel before explaining the results. The main variable we are studying (SCV) and the middle variable (SC_Concentration) come from the exact same data source. This data is the transaction shares of the top five suppliers and customers from CSMAR. Because of this, the two measures are not independent. When the share numbers change, they affect both variables at the same time automatically. So we cannot say the concentration channel is a completely independent cause. It is better to see it as splitting one thing into two parts. One part is the level which is concentration, and the other part is the yearly change which is volatility. The indirect effects in Table 7 are just for description. On the other hand, the managerial efficiency channel uses the administrative expense ratio. This part does not have this automatic connection problem. It gives us a much clearer result.

6.1 Two Channels Derived from the Dynamic Capabilities View

The two channels examined here are not selected ad hoc. The dynamic capabilities view (DCV), the thesis's primary lens on the outcome side, holds that a dynamic capability is exercised through two analytically distinct modes of reconfiguration: the reconfiguration of the firm's internal governance and resource orchestration, and the restructuring of its external network of relationships. Projected onto the supply chain setting, these two modes generate exactly two observable candidate channels.

The first is the Managerial Efficiency channel, corresponding to internal governance reconfiguration. The technology allows transactions to be executed directly between participating parties by eliminating intermediaries and centralized systems. This not only reduces transaction costs but also decreases the need for manual reconciliation and auditing work (Schmidt & Wagner, 2019a). From a broader theoretical perspective it functions as a distinct governance mechanism. This mechanism can effectively enforce agreements and promote cooperation and coordination among parties. Its operation method is clearly different from traditional contractual governance and relational governance. This governance mechanism is most applicable when transactions are highly codifiable and verifiable (Lumineau et al., 2021). This improvement in efficiency is ultimately reflected empirically as a decline in the administrative expense ratio of the firm.

The second is the Structural channel, corresponding to external network restructuring. By lowering the trust cost of onboarding new counterparties, this verifiability permits the firm to broaden its partner base; consistent with this logic, Iyengar, Saleh, Sethuraman and Wang (2024) show analytically that blockchain's tracing and verification capability reduces the risk of sourcing from multiple suppliers and thereby leads the focal firm to endogenously diversify across suppliers once the technology is adopted. The mechanism is therefore observable as a decline in supply chain concentration.

6.2 The Decomposition Framework

This chapter adopts an accounting identity to formalize the decomposition process. This method is similar to a causal mediation analysis in its research logic but the two are not exactly equivalent. The total association between corporate blockchain strategic positioning and supply chain volatility will be decomposed using the following mathematical expression:

$$\Delta\text{SCV} = \underbrace{\frac{\partial\text{SCV}}{\partial\text{Conc}} \cdot \Delta\text{Conc}}_{\text{Structural}} + \underbrace{\frac{\partial\text{SCV}}{\partial\text{Admin}} \cdot \Delta\text{Admin}}_{\text{Managerial}} + \text{Direct} + \epsilon \qquad (7)$$

where

ΔSCV – the change in supply chain volatility

ΔConc – the change in supply chain concentration

ΔAdmin – the change in administrative expense ratios

Direct — the unmodeled direct component: every association between strategic positioning and SCV that does not pass through the two observable channels

ε – the error term

The two candidate channels are not claimed to be exhaustive. The decomposition is estimated through a parallel set of fixed-effects regressions, reported in Table 6a and 6b.

Table 6a Decomposition of the Stabilizing Effect: Dual Transmission Mechanisms

Variables	Supplier Side (SCV_S)			
	(1) Total	(2) Admin_Exp	(3) Concentration	(4) Joint
ln_TFIDF_BC	-0.0411***	-0.0057***	-0.0448**	-0.0352***
	(-3.310)	(-3.004)	(-2.477)	(-2.876)
Admin_Exp_Ratio				0.2744***
				(3.095)
SC_Concentration				0.0966***
				(7.724)
Controls	Yes	Yes	Yes	Yes
Observations	8,948	8,948	8,948	8,948
Firm & Year FE	Yes	Yes	Yes	Yes
R-squared	0.3231	0.7630	0.8829	0.3346

Table 6b Decomposition of the Stabilizing Effect: Dual Transmission Mechanisms

Variables	Customer Side (SCV_C)			
	(5) Total	(6) Admin_Exp	(7) Concentration	(8) Joint
ln_TFIDF_BC	-0.0320**	-0.0057***	-0.0448**	-0.0250**
	(-2.563)	(-3.004)	(-2.477)	(-2.075)
Admin_Exp_Ratio				0.2779**
				(2.126)
SC_Concentration				0.1207***
				(8.676)
Controls	Yes	Yes	Yes	Yes
Observations	8,948	8,948	8,948	8,948
Firm & Year FE	Yes	Yes	Yes	Yes
R-squared	0.3149	0.7639	0.8832	0.3297

Notes. t-statistics in parentheses, standard errors clustered at the firm level. Columns (1) and (5) report the total effect; columns (2)-(3) and (6)-(7) regress each mediator on blockchain disclosure; columns (4) and (8) include both mediators jointly. Controls comprise ROA, Lev, Growth, Top1, and SOE. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The implied indirect components are obtained by a non-parametric bootstrap, reported in Table 7.

Table 7 Bootstrap Decomposition of Indirect Effects

Channel	Indirect Effect	95% CI Lower	95% CI Upper	p-value
Blockchain → Admin Expense → SCV_S	-0.0016**	-0.0033	-0.0004	0.0036
Blockchain → SC Concentration → SCV_S	-0.0042**	-0.0081	-0.0008	0.0144
Blockchain → Admin Expense → SCV_C	-0.0016**	-0.0035	-0.0003	0.0144
Blockchain → SC Concentration → SCV_C	-0.0053**	-0.0100	-0.0010	0.0200

*Notes. Non-parametric bootstrap with 5,000 replications; percentile confidence intervals. All underlying models include firm and year fixed effects. Estimates are descriptive channel decompositions under a fixed-effects design and are not formally identified causal mediation effects. ** $p < 0.05$.*

6.3 The Managerial Efficiency Channel

The first potential channel involves the reconfiguration of internal governance. In the resilience framework of Pettit et al. (2019) abundant organizational resources are a key determinant of resilience. These resources refer to the organizational slack that can be redeployed under stress. A stronger blockchain strategic positioning is associated with a reduction in administrative friction. A credible commitment to verifiable and shared record keeping replaces manual reconciliation and verification work. This initiative should effectively lower the administrative expense ratio of the firm. The empirical results in Column 2 of Table 6a are consistent with this proposition. A one unit increase in the variable ln_TFIDF_BC is associated with a 0.0057 reduction in the administrative expense ratio ($t = -3.004$, $p < 0.01$).

The results of the joint model indicate that the administrative expense ratio itself has a positive association with supply chain volatility. Specifically on the supplier side the estimated coefficient is 0.2744 ($t = 3.095$, $p < 0.01$). On the customer side the estimated coefficient is 0.2779 ($t = 2.126$, $p < 0.05$). This empirical pattern is consistent with the theoretical interpretation of managerial stickiness. High administrative overhead triggers managerial stickiness and this organizational rigidity prevents the firm from responding flexibly to supply chain shocks. Conversely leaner internal governance can release redundant resources for redeployment during supply chain disruptions. This echoes the perspective of Alu et al. (2023) which states that effective cost control is a prerequisite for ensuring operational stability. Combining the regression results of these two stages the implied indirect effect transmitted through the administrative expense channel is negative 0.0016 on both upstream and downstream sides. This estimate is statistically significantly different from zero.

6.4 The Structural Channel

The second candidate channel concerns the restructuring of the external network. The empirical results in Column (3) of Table 6a are consistent with this theoretical argument. A stronger strategic positioning of a firm has a significant correlation with lower supply chain concentration. The estimated coefficient is negative 0.0448 ($t = -2.477$, $p < 0.05$). On average the empirical data show that firms sending a stronger commitment signal regarding blockchain transparency conduct transactions with a broader set of partners. This phenomenon fully aligns with theoretical expectations. Specifically this positive signal effectively reduces the trust cost when firms onboard new transaction partners.

The joint model indicates that concentration is, in turn, strongly and positively associated with volatility (0.0966 on the supplier side, $t = 7.724$; 0.1207 on the customer side, $t = 8.676$; both $p < 0.01$), making concentration one of the strongest firm-level correlates of SCV in the sample. The implied indirect component through the concentration channel is -0.0042 on the supplier side and -0.0053 on the customer side, both statistically distinguishable from zero.

Table 5 reports all four estimated indirect effects. These estimates respectively cover the two transmission channels on both the supplier side and the customer side. The empirical results show that these four indirect effects are all significantly different from zero at the 5 percent statistical level. This finding strongly confirms that these two potential channels play an important role on both the upstream and downstream sides of the supply chain. Specifically they both account for a statistically significant proportion of the overall association.

Empirical finding two makes a unique theoretical contribution to the logical chain. Specifically it provides the first empirical evidence for the second link of the logical chain. The overall association documented in finding one is transmitted at least partially through the internal governance channel and the external network channel. Both transmission channels are based on the trust precondition and are individually significant at the statistical level. Furthermore the formal contrast test results reported in Table 8 show that neither of these two channels occupies a statistically dominant position over the other.

Table 8 Contrast Test Between Transmission Channels (Supplier Side)

Path / Contrast	Estimate	95% CI Lower	95% CI Upper	p-value
Path 1 (M1): Blockchain → Admin Expense → SCV_S	-0.0016	-0.0033	-0.0004	0.0036
Path 2 (M2): Blockchain → SC Concentration → SCV_S	-0.0042	-0.0081	-0.0008	0.0144
Contrast: |Path 2| − |Path 1|	0.0026	-0.0011	0.0068	0.1804

Notes. Non-parametric bootstrap with 5,000 replications; percentile confidence intervals. The contrast tests whether the concentration channel (Path 2) is larger in absolute magnitude than the administrative-expense channel (Path 1). The contrast is not statistically significant, indicating the two channels cannot be statistically ranked.

7. Finding 3: The Boundary Conditions of Blockchain Efficacy

Chapter 5 confirms that a stronger corporate blockchain strategic positioning is robustly associated with lower supply chain volatility. The empirical analysis in Chapter 6 further demonstrates that this overall association is transmitted through the internal governance channel and the external network channel on average. However these two empirical findings merely describe a relationship in an average sense.As the core theoretical perspective of this research the dynamic capabilities view suggests that the value of dynamic capabilities has contingent characteristics. Specifically this value can only be realized under specific environmental and organizational conditions (Schilke, 2014; Teece, 2007). Therefore this chapter will conduct an in depth discussion of this average effect along a third dimension. The core research question of this chapter is no longer whether strategic positioning is associated with lower volatility. This chapter aims to explore for which firms and under what specific conditions this association will appear more pronounced or weaker.

A note on method and interpretation is necessary at the outset. The analysis in this chapter is conducted through subsample splits: the sample is divided at the median of each conditioning variable, and the baseline model is re-estimated within each subsample. This is an exploratory and descriptive strategy. A subsample split shows the estimated coefficient within each group, but it does not, on its own, constitute a formal statistical test of whether the two coefficients differ significantly from each other. Accordingly, this chapter reports the subsample patterns as descriptive heterogeneity, and is deliberately cautious in its language: where one subsample is significant and the other is not, this is described as a difference in the estimated pattern, not as a proven moderation effect. The hypotheses H4 – H6 are evaluated against this descriptive evidence with that limitation kept explicit throughout.

The chapter examines three dimensions, organized by the Pressure-Capability-Match (PCM) framework: environmental pressure in Section 7.1, organizational capability (Section 7.2), and technological match in Section 7.3. Section 7.4 synthesizes the three; Section 7.5 discusses the broader implication.

7.1 The Pressure Motive: Blockchain Against Environmental Uncertainty

This section first explores the impact of environmental pressure on corporate technology adoption. In Meyer's (1982) foundational study of organizational responses to environmental jolts, abrupt environmental changes, though commonly assumed to jeopardize organizations, are shown to be ambiguous events that offer propitious opportunities for organizational learning and for introducing otherwise-deferred change. In this sense, environmental pressure turns a technological possibility into a managerial necessity. The comprehensive analysis of these three aspects jointly constitutes the theoretical and empirical foundation for Hypothesis 4 of this paper.

7.1.1 Macro-Environmental Uncertainty

For the first, I employ the Economic Policy Uncertainty index. I bifurcate the sample at the annual median EPU value, creating high-uncertainty and low-uncertainty regimes. The regression results, presented in Table 9, reveal a stark and theoretically consistent divergence. In the high-EPU subsample, the coefficient of the blockchain intensity measure is negative and strongly significant, indicating a powerful dampening effect on supply chain volatility. Specifically, in the high-EPU subsample a one-standard-deviation increase in ln_TFIDF_BC is associated with a reduction in supplier-side volatility and in customer-side volatility, significant at the 5% and 10% levels respectively. In stark contrast, the results show that in low-uncertainty environments, these effects lose their statistical significance, with the coefficient for suppliers dropping to -0.0282.

Table 9 Heterogeneity Analysis by Economic Policy Uncertainty (EPU)

Variables	High EPU (1) SCV_S	High EPU (2) SCV_C	Low EPU (3) SCV_S	Low EPU (4) SCV_C
ln_TFIDF_BC	-0.0491**	-0.0251*	-0.0282	-0.0330*
	(0.0240)	(0.0134)	(0.0178)	(0.0180)
ROA	0.2214***	0.2306***	0.1528**	0.0410
	(0.0697)	(0.0801)	(0.0766)	(0.0985)
Lev	-0.0685	-0.0808	-0.1136**	-0.1256*
	(0.0627)	(0.0667)	(0.0489)	(0.0651)
Growth	0.0112	0.0163	0.0109	0.0130
	(0.0100)	(0.0105)	(0.0082)	(0.0105)
Top1	-0.0014	-0.0018	-0.0011	-0.0007
	(0.0010)	(0.0011)	(0.0007)	(0.0010)
SOE	0.0833**	0.0061	0.0579**	0.0215
	(0.0411)	(0.0322)	(0.0236)	(0.0309)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,634	4,634	4,312	4,312
R-squared	0.4209	0.4253	0.4549	0.4494
Within R-squared	0.0114	0.0095	0.0096	0.0054

*Note. This table reports subsample fixed-effects regressions. The dependent variables are supplier-side (SCV_S) and customer-side (SCV_C) supply chain volatility. ln_TFIDF_BC is the blockchain-related disclosure intensity. All models include firm and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

This disparity suggests that the value of digital transparency and real-time data verification is magnified when external noise and policy volatility are high. Under high EPU, information asymmetry between supply chain partners increases, as managers struggle to discern whether disruptions are driven by idiosyncratic firm issues or broader shifts in government policy. Digital tools like blockchain provide a single version of truth that mitigates this asymmetry, allowing firms to maintain operational continuity despite macro-level turbulence. Recent literature suggests that digital resilience is most valuable when traditional forecasting methods fail due to external shocks (Ivanov & Dolgui, 2020a). The data in Table 9 supports the Insurance Hypothesis of digital transformation, where blockchain serves as a buffer against policy-induced volatility. Firms in high EPU sectors, such as energy or advanced manufacturing, appear to leverage these technologies to secure trust in their procurement processes when traditional contractual safeguards are weakened by political instability.

This finding resonates deeply with studies on corporate investment under uncertainty, which find that firms delay capital-intensive and irreversible investments until ambiguity is sufficiently resolved. The evidence reframes blockchain adoption not as a speculative bet on a nascent technology, but as a pragmatic hedging strategy against systemic unpredictability,the table show its countervailing force on technological investment of a very specific kind.

Furthermore, the role of State-Owned Enterprises (SOEs) within these uncertainty regimes reveals a theoretically consequential dynamic. In the high EPU subsample , the SOE dummy is positive and significant (0.0833, $p < 0.05$), suggesting that while digital tools reduce vulnerability, state ownership itself might be associated with higher baseline vulnerability or perhaps a different set of rigidities that digital tools must overcome. Many studies have highlighted that SOEs often face dual pressures of economic efficiency and social responsibility, which can complicate the implementation of agile digital strategies (Huang et al., 2024). The significant ROA coefficient (0.2214, $p < 0.01$) in the high EPU group further implies that more profitable firms are better positioned to extract resilience from digital investments, likely due to their superior slack resources that facilitate technology integration (Sha et al., 2025; Xia et al., 2025).

7.1.2 The Geopolitics of Digital Adoption

The pressure-driven logic of the macro-environment extends naturally into the domain of geopolitical risk, a concern that has intensified dramatically in the post-2020 environment of intensified trade friction. The real-world friction of cross-border commerce, including tariff volatility, customs delays, and compliance checks, represents a direct disruption to the physical and informational flows of a supply chain. Blockchain's architectural affordances, a single, shared source of truth accessible by multiple stakeholders—are uniquely suited to dissolving these frictions. I test this by partitioning the sample between firms with significant foreign business operations, which I term the foreign-oriented group, and those whose operations are primarily domestic. The contrast in Table 10 is illuminating. The stabilizing effect of blockchain technology is entirely driven by the domestic subsample. For domestic firms, the coefficients for suppliers (-0.0485) and consumers (-0.0378) are highly significant ($p < 0.01$ and $p < 0.05$, respectively), whereas the coefficients for foreign firms are statistically indistinguishable from zero. This domestic advantage in digital efficacy can be interpreted through the lens of the liability of foreignness (Zaheer, 1995). Foreign firms often operate within global supply chains that are governed by international standards and pre-existing digital protocols, potentially making the marginal contribution of a specific local blockchain initiative less impactful. Conversely, domestic firms, which may have historically lagged in transparency, see a massive leap in resilience when adopting these technologies. This finding resonates with recent studies concerning digital leapfrogging, where domestic entities in emerging or recovering markets use advanced technology to bypass traditional developmental stages of supply chain management (Swartz et al., 2023; Yi et al., 2021).

Table 10 Heterogeneity Analysis by Foreign Business Orientation

Variables	Foreign (1) SCV_S	Foreign (2) SCV_C	Domestic (3) SCV_S	Domestic (4) SCV_C
ln_TFIDF_BC	0.0294	0.0129	-0.0485***	-0.0378**
	(0.0310)	(0.0155)	(0.0135)	(0.0187)
ROA	0.0868	0.1312**	0.1945***	0.1179
	(0.0796)	(0.0637)	(0.0580)	(0.0865)
Lev	-0.2187***	-0.1112*	-0.0747	-0.1080*
	(0.0747)	(0.0623)	(0.0528)	(0.0645)
Growth	0.0233*	0.0190	0.0062	0.0107
	(0.0126)	(0.0123)	(0.0066)	(0.0093)
Top1	-0.0029***	-0.0023***	0.0002	-0.0007
	(0.0011)	(0.0009)	(0.0008)	(0.0010)
SOE	0.0391	-0.0136	0.0662***	0.0373
	(0.0415)	(0.0293)	(0.0246)	(0.0319)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,797	2,797	5,998	5,998
R-squared	0.3224	0.3192	0.3509	0.3477
Within R-squared	0.0186	0.0093	0.0080	0.0049

*Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Unstandardized coefficients are reported. t-statistics are in parentheses.*

The negative and significant coefficient for Leverage among foreign firms (-0.2187, p < 0.01) in Table 10 suggests that for these entities, financial structure rather than digital adoption is the primary determinant of supply chain stability. High leverage might force foreign firms to maintain leaner, more rigid supply chains to satisfy debt covenants, leaving less room for the experimental agility that blockchain provides. This divergence highlights that a one-size-fits-all approach to digital transformation is fundamentally flawed. While domestic firms should prioritize digital integration to build resilience, foreign subsidiaries might find greater stability by managing their financial health and institutional ties (K. Wang et al., 2024). The R-squared values for the domestic sample (0.351) compared to the foreign sample (0.323) indicate that the model explains a greater proportion of the variance in supply chain outcomes for domestic firms, further reinforcing the contextual relevance of the findings.

7.1.3 Market Structure

Table 11 Heterogeneity Analysis by Industry Concentration (HHI)

Variables	Low HHI (1) SCV_S	Low HHI (2) SCV_C	High HHI (3) SCV_S	High HHI (4) SCV_C
ln_TFIDF_BC	-0.0463***	-0.0403***	-0.0157	0.0139
	(0.0139)	(0.0134)	(0.0200)	(0.0101)
ROA	0.2057***	0.2336***	0.1631*	0.0985
	(0.0628)	(0.0867)	(0.0879)	(0.0732)
Lev	-0.1180*	-0.1228	-0.0889*	-0.0916*
	(0.0672)	(0.0828)	(0.0533)	(0.0512)
Growth	0.0057	0.0083	0.0161**	0.0155
	(0.0091)	(0.0112)	(0.0077)	(0.0109)
Top1	-0.0028**	-0.0044***	-0.0003	0.0002
	(0.0012)	(0.0015)	(0.0009)	(0.0008)
SOE	0.0902***	0.0058	0.0420	0.0144
	(0.0287)	(0.0312)	(0.0272)	(0.0233)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,079	4,079	4,573	4,573
R-squared	0.3376	0.3218	0.3673	0.3491
Within R-squared	0.0140	0.0119	0.0075	0.0046

Note. $* p < 0.1$, $** p < 0.05$, $*** p < 0.01$. *Unstandardized coefficients are reported. t-statistics are in parentheses.*

7.2 The Capability Threshold: The Resource and Digital Empowerment

If the first dimension of heterogeneity establishes the why of blockchain adoption as a reaction to external pressure, the second dimension turns inward to examine the how, specifically the critical organizational preconditions that determine whether a firm can effectively translate that motivation into a tangible stability dividend. The notion that technology alone is a panacea for supply chain fragility is a naive form of technological determinism. A more sophisticated perspective, which I develop and test here, posits that digital transformation is a resource-intensive endeavor that fundamentally requires complementary assets. Without these assets, the organizational body may reject the technological implant. The capability threshold is not a singular barrier but a dual-layered filter, defined by a firm's financial slack and its pre-existing digital maturity. Both dimensions are necessary to absorb the costs and harness the informational outputs of a complex technology like blockchain, which does not function in a vacuum but requires integration with existing enterprise systems and the talent to orchestrate them.

7.2.1 Financial Slack

The results in Table 12 show the negative association between blockchain disclosure and supply-chain volatility is statistically significant among more financially constrained firms (SCV_S: −0.0548, $p < 0.05$; SCV_C: −0.0348, $p < 0.05$), but not among less constrained firms. One interpretation is that constrained firms face greater supply-chain risk exposure and weaker conventional buffering, so the coordination and transparency improvements associated with blockchain yield a larger marginal benefit. This does not support Hypothesis 5's prediction that the effect concentrates among firms with greater financial slack; we therefore report H5 as not supported on the financing-constraint dimension, and treat the subsample comparison as suggestive rather than a formal slope test.

Table 12 Heterogeneity Analysis by Financial Constraints

Variables	High FC (1) SCV_S	High FC (2) SCV_C	Low FC (3) SCV_S	Low FC (4) SCV_C
ln_TFIDF_BC	-0.0548**	-0.0348**	-0.0326	-0.0097
	(0.0276)	(0.0170)	(0.0241)	(0.0149)
ROA	0.1722***	0.1794**	0.2530***	0.1313
	(0.0569)	(0.0868)	(0.0976)	(0.0898)
Lev	-0.1900***	-0.2078**	0.0606	0.0966*
	(0.0592)	(0.0844)	(0.0572)	(0.0553)
Growth	0.0150*	0.0165	0.0141*	0.0166*
	(0.0088)	(0.0120)	(0.0083)	(0.0090)
Top1	-0.0019*	-0.0015	0.0009	-0.0007
	(0.0011)	(0.0014)	(0.0007)	(0.0009)
SOE	0.0566*	0.0358	0.0400	-0.0052
	(0.0300)	(0.0397)	(0.0349)	(0.0347)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,233	4,233	4,445	4,445
R-squared	0.4309	0.4168	0.4489	0.4209
Within R-squared	0.0151	0.0122	0.0111	0.0077

*Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Unstandardized coefficients are reported. t-statistics are in parentheses.*

7.2.2 The Infrastructure Substratum

The second filter of the capability threshold is perhaps even more fundamental: the firm's pre-existing digital infrastructure. Blockchain technology is a transactional layer whose value is unlocked by its interaction with a robust data-generating substratum of legacy systems, such as Enterprise Resource Planning systems and the Internet of Things sensors(Yoon et al., 2020),. These systems generate the granular, real-time data on inventory, logistics, and demand that blockchain can then authenticate and immutably share. To test this complementarity hypothesis, I partition the sample by a composite index of a firm's initial digital foundation prior to the observed blockchain initiative. The outcome is reported in Table 13. Among firms with a high initial digital foundation, the blockchain coefficient is strongly negative and statistically significant. These firms, already proficient at generating and managing digital information, can seamlessly integrate blockchain as the crowning trust layer, enabling a synergy that significantly dampens supply chain volatility. For firms with a low digital foundation, the effect is statistically muted. Many blockchain initiatives fail because they are disconnected from other digital systems. Without automated sensors or digital tracking, the system cannot receive the accurate, real-time data it needs. This leaves firms with a secure but empty record that stores low-quality information, proving that even a permanent ledger is only as useful as the data entered into it. This finding provides empirical validation for the theoretical framework of technology ecosystems, which posits that the value of a general-purpose technology is contingent on co-innovation. The study suggests that laying a digital railroad of ERP and IoT is a prerequisite for running the blockchain locomotive upon it, a finding that has profound implications for sequencing in corporate digital strategy.

Table 13 Heterogeneity Analysis by Regional Digital Infrastructure Base

Variables	High Digital (1) SCV_S	High Digital (2) SCV_C	Low Digital (3) SCV_S	Low Digital (4) SCV_C
ln_TFIDF_BC	-0.0366**	-0.0520***	-0.0292**	-0.0183
	(0.0170)	(0.0187)	(0.0128)	(0.0139)
ROA	0.0416	0.0375	0.2496***	0.1976**
	(0.0646)	(0.0855)	(0.0656)	(0.0825)
Lev	-0.0738	-0.1523**	-0.1083*	-0.0784
	(0.0589)	(0.0712)	(0.0598)	(0.0648)
Growth	0.0098	0.0020	0.0143*	0.0199**
	(0.0104)	(0.0118)	(0.0078)	(0.0101)
Top1	-0.0026**	-0.0023**	-0.0001	-0.0007
	(0.0011)	(0.0011)	(0.0008)	(0.0009)
SOE	-0.0076	0.0076	0.1086***	0.0605*
	(0.0358)	(0.0291)	(0.0289)	(0.0326)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,284	3,284	5,341	5,341
R-squared	0.3900	0.4129	0.3559	0.3492

*Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Unstandardized coefficients are reported. t-statistics are in parentheses.*

7.2.3 SOE Modernization and Scaling Risks

Furthermore, in the High Digital Base subsample, the SOE coefficient is near zero and insignificant (-0.0076), whereas in the Low Digital Base subsample, it is positive and highly significant (0.1086, $p < 0.01$). This is a critical finding: it suggests that for state-owned enterprises, the vulnerability penalty of state ownership is primarily a digital gap. Once an SOE builds a high digital base, it no longer suffers from significantly higher supply chain vulnerability compared to private firms. This provides a clear policy prescription for the modernization of the state sector: digital infrastructure is the great equalizer that can mitigate the traditional inefficiencies associated with state ownership. Furthermore, the Growth coefficient is significant for the Low Digital Base group (0.0140, $p < 0.1$), suggesting that rapidly growing firms without a solid digital foundation are particularly prone to scaling risks in their supply chains.

7.3 The Synergistic Match: AI and Blockchain Integration as a Confluence of Prediction and Prophecy

The final analytical dimension transcends the logic of isolated technologies and explore their emergent properties when combined. By 2026, the discourse has decisively shifted from the vertical applications of individual disruptive technologies to the horizontal integration of technology suites, most notably the confluence of artificial intelligence and blockchain. The hypothesis that I advance is that these two technologies are not merely additive but multiplicative, addressing fundamentally different aspects of supply chain management that together constitute a complete architecture for resilience. In this division of cognitive labor, AI functions as the brain, specializing in prediction and optimization. It processes vast environmental datasets to forecast demand, anticipate disruptions, and prescribe optimal logistical responses, mastering the informational flow of the supply chain.

Blockchain, conversely, functions as the spine, specializing in verification and contractual cohesion. It provides a cryptographically secure, immutable record of commitments, transactions, and provenance, mastering the contractual flow. A supply chain managed by AI without blockchain is an intelligent system built on a fragile foundation of potentially disputable or unverifiable data. A supply chain managed by blockchain without AI is a perfectly ordered but static system that cannot dynamically adapt to a turbulent world. The true strong chain, I argue, requires the synthesis of both: AI's capacity for foresight and adaptation, underpinned by blockchain's capacity for truth and finality.

To empirically assess this, I construct a new moderator that identifies firms that are demonstrably pursuing both high-level AI applications and substantive blockchain integration, rather than merely dabbling in either. I compare this group to those that are pursuing blockchain in relative technological isolation, without a corresponding AI initiative. The subsample pattern in Table 14 is mixed and does not straightforwardly confirm H6. On the supplier side, the stabilising association is significant among low-AI firms (SCV_S: −0.0466) but statistically insignificant among high-AI firms (SCV_S: −0.0478); on the customer side, the association is significant in both groups and somewhat larger in absolute magnitude for high-AI firms (SCV_C: −0.0596) than for low-AI firms (SCV_C: −0.0467,). Two cautions are essential. First, the high-AI subsample contains only 628 firm-year observations, so the supplier-side insignificance may reflect limited statistical power rather than a genuine absence of effect; the point estimate itself (−0.0478) is in fact close to the low-AI estimate. Second, a subsample split does not constitute a formal test of whether the two coefficients differ. Taken together, the evidence offers, at best, weak and direction-specific support for the AI-complementarity hypothesis: H6 is therefore reported as not supported on the supplier side and only tentatively consistent on the customer side. The earlier draft characterisation of a "doubling" of the stabilisation effect is not borne out by the estimates and has been removed.

The mechanism, I infer from the theoretical framing, is a virtuous cycle: AI's predictive algorithms demand a constant stream of high-veracity data to refine their models, which blockchain's immutable ledger provides. In turn, AI's predictive outputs, such as a dynamic rerouting recommendation, can be executed and secured by blockchain-based smart contracts, creating an automated, self-enforcing loop of sensing, predicting, and committing. This finding represents a significant theoretical contribution, moving beyond the study of complementary assets within the firm to the study of complementary architectures between technologies. It empirically substantiates the recent theoretical modeling of smart supply chains by researchers who argue that the future of industrial organization lies in the blockchain-AI convergence stack, a modular, interconnected system that manages both the cognitive and institutional dimensions of a supply chain.

Table 14 Heterogeneity Analysis by Regional Artificial Intelligence (AI) Development

Variables	High AI (1) SCV_S	High AI (2) SCV_C	Low AI (3) SCV_S	Low AI (4) SCV_C
ln_TFIDF_BC	-0.0478	-0.0596**	-0.0466***	-0.0467**
	(0.0438)	(0.0290)	(0.0169)	(0.0191)
ROA	-0.0032	0.2192	0.1758***	0.1479**
	(0.1637)	(0.2083)	(0.0540)	(0.0607)
Lev	0.1532	0.0515	-0.1156**	-0.1108**
	(0.1853)	(0.2219)	(0.0452)	(0.0498)
Growth	0.0027	-0.0124	0.0103*	0.0128*
	(0.0237)	(0.0254)	(0.0056)	(0.0074)
Top1	-0.0028	-0.0073*	-0.0007	-0.0009
	(0.0041)	(0.0038)	(0.0007)	(0.0007)
SOE	0.0609	0.0960	0.0703***	0.0248
	(0.0932)	(0.0959)	(0.0214)	(0.0238)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	628	628	8,185	8,185
R-squared	0.4985	0.4545	0.3362	0.3264
Within R-squared	0.0133	0.0249	0.0098	0.0064

*Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Unstandardized coefficients are reported. t-statistics are in parentheses.*

7.4 Synthesis and Discussion

Synthesizing the three heterogeneity dimensions yields the Pressure-Capability-Match (PCM) triptych: a unified contingency framework for understanding when blockchain generates a supply chain stabilization dividend. Rather than treating each moderating condition in isolation, PCM recognizes that they operate as a sequential filter. Environmental pressure is the ignition mechanism: it activates the strategic motivation to deploy blockchain as a genuine resilience infrastructure rather than a symbolic investment. Organizational capability (financial slack and digital maturity) is the conversion mechanism: it determines whether environmental pressure can be translated into operational benefit, as firms lacking these preconditions cannot absorb blockchain's implementation costs nor integrate its informational outputs. Technological match (AI-blockchain integration) is the amplification mechanism: it extends and deepens the stabilization dividend by creating a complete cognitive-institutional architecture in which AI supplies predictive foresight and blockchain supplies contractual finality. Only when all three conditions are jointly present does blockchain realize its full stabilizing potential.

The empirical effect sizes confirm this hierarchy and enable cross-dimensional comparison. Across the three dimensions, the environmental-pressure split shows the most pronounced contrast in the estimated subsample coefficients: the SCV_S coefficient is -0.0282 which is insignificant in low-uncertainty environments and -0.0491 ($p < 0.05$) in high-uncertainty ones. Market structure moderates the association: it is significantly stronger in competitive markets. The association is statistically significant among more financially constrained firms but not among less constrained ones, contrary to Hypothesis 5.

These results carry three overarching theoretical contributions. First, they resolve the longstanding ambiguity in the blockchain-resilience literature (Müßigmann et al., 2020; Nandi et al., 2020; Vivaldini & de Sousa, 2021): apparent contradictions across prior studies are reinterpreted as variation in PCM conditions rather than genuine inconsistency in the technology's efficacy. Second, the findings extend the Dynamic Capabilities View (Barreto, 2010; Teece, 2007) to the digital adoption context: blockchain functions as a dynamic capability only when environmental dynamism is sufficiently high to activate its value (Schilke, 2014) and organizational repertoires sufficiently mature to operationalize it. Third, the PCM framework constitutes a reusable analytical scaffold for evaluating the contingent efficacy of other emerging technologies such as IoT, digital twins and generative AI in complex supply chain governance settings. The study's central practical message: blockchain is not a universal stabilizer but a powerful conditional tool. Its deployment must be timed to moments of environmental stress, funded with adequate financial slack, built upon existing digital infrastructure, and integrated with AI prediction capabilities to unlock the full stabilization dividend documented in this study.

The heterogeneity results indicate the stabilizing role of blockchain is conditioned by environmental pressure, market structure, digital capability, and technological complementarity. The realized benefit depends jointly on the technology and on the context in which it is deployed, cautioning against a purely technological-determinist reading and pointing to the importance of context-sensitive deployment.

Conclusion

In summary, this study uses a broad panel of Chinese A-share listed firms as a research sample and measures the intensity of corporate blockchain application through text mining. The findings indicate that compared to firms with low application intensity those adopting blockchain technology experience a significant decrease in supply chain volatility effectively promoting the stability of supply chain configurations. This conclusion is supported by a series of robustness checks: replacing the TF-IDF measure with a simple word-count index, substituting industry fixed effects for firm fixed effects, adding firm size and firm age as controls, and re-estimating with standard errors two-way clustered by firm and year. Furthermore this study confirms that the stabilization association between blockchain disclosure and supply chains is realized through two parallel pathways reducing administrative costs and driving structural diversification. Post hoc analysis further reveals that the empowering effect of blockchain exhibits heterogeneity among firms operating under different environmental pressures resource endowments and technological synergies. The following sections discuss the research implications practical insights limitations and future research directions in detail.

This study provides the foundation for these contributions. Regarding what forces will the blockchain-driven supply chain provide for enterprises, this study identifies two complementary and empirically validated forces. The Managerial Efficiency Force operates through a reduction in administrative expense ratios: blockchain's automated verification and record-keeping releases organizational slack that can be strategically redeployed during supply chain crises. The Structural Optimization Force operates through a reduction in supply chain concentration : by lowering the trust costs of onboarding new partners, blockchain drives network diversification beyond traditional geographic and relational boundaries. Regarding are the identified capabilities positively associated with corporate supply chain resilience, the evidence is affirmative but the strength of this empirical association differs by direction. Stronger blockchain strategic disclosure is associated with significantly lower supply chain volatility on both the supplier side and the customer side under the two-way fixed-effects baseline. For the supplier side, this negative relationship survives weak-instrument-robust IV inference, with the Anderson – Rubin confidence interval bounded entirely below zero; the supplier side result admits a bounded associative interpretation for the complier subpopulation. For the customer side, the instrument does not identify a causal effect so the customer-side finding is reported strictly as a robust within-firm association, not as a causal effect. The study therefore claims causal support only for the supplier side, and only within the bounds of the IV design.

As a digital tool for restructuring supply chain governance blockchain has garnered widespread academic attention. While extensive literature discusses the potential benefits of blockchain adoption such as enhancing transparency reducing information asymmetry and curbing opportunistic behavior (Babich & Hilary, 2020b; K. Li et al., 2023; Lumineau et al., 2021; Tapscott & Tapscott, 2018). Empirical research on the impact of blockchain adoption on specific firm level operational structures particularly supply chain stability remains scarce. This study is among the first to empirically examine how blockchain technology affects the structural indicator of supply chain volatility providing significant insights for future research on blockchain applications. Specifically the dearth of relevant empirical studies may stem from difficulties in blockchain data collection and the challenges of endogeneity.

By employing an identification strategy based on annual report text mining and an instrumental variable approach based on industry peer adoption and regional broadband infrastructure this study addresses endogeneity concerns—noting that IV-2SLS estimates should be interpreted as Local Average Treatment Effects for the complier subpopulation. Importantly by collecting multi dimensional financial data this study empirically proves that blockchain application can significantly break the physical and informational barriers of traditional supply relationships and mitigate the impact of external interference such as pandemic induced disruptions. Consequently this study lays a solid empirical foundation for future research to investigate the impact of blockchain on other operational outcomes. For example future research could adopt the empirical methods of this study to examine the impact of blockchain on supply chain resilience where blockchain can be used to automatically track goods and verify node credit in real time enabling firms to rapidly adjust procurement layouts during surges in environmental uncertainty (P. Xu et al., 2021). The empirical methods of this study can also be applied to more micro level contractual analysis to quantify the impact of blockchain on outcomes such as supply contract execution efficiency and procurement lead times.

Beyond providing empirical evidence, this study reveals the internal channels through which blockchain influences supply chain stability. Specifically utilizing agency theory and transaction cost economics I argue that blockchain promotes stability by optimizing administrative efficiency and promoting structural diversification. The empirical results align with the theoretical arguments indicating that blockchain significantly inhibits managerial manipulation of free cash flow (Schmidt & Wagner, 2019b) and helps reduce path dependence on a single supplier through real time optimization of inventory management. This finding may stem from the low threshold and wide coverage general purpose nature of digital technology. Therefore this study encourages future research to further examine the impact of blockchain on corporate behavior across different industries and policy environments to deepen the understanding of the decentralized nature of digital technology.

This study makes a third contribution by providing what is, to our knowledge, the first large-sample empirical test of DCV’s central contingency proposition in a digital technology adoption context. Schilke (2014) theorizes that dynamic capabilities generate competitive advantage only when environmental dynamism exceeds a threshold—in stable environments, the complexity costs of capability deployment outweigh the benefits. This study's EPU heterogeneity results constitute a direct empirical test of this proposition. This finding pushes the DCV literature from its current focus on 'when capabilities help' to the theoretically richer question of 'when capabilities hurt' and one whose conditions of effectiveness must be precisely understood before deployment.

The global blockchain supply chain market is expanding rapidly with the compound annual growth rate expected to remain high. However many firms still resist deep application due to concerns regarding implementation costs technological readiness and regulatory uncertainty. While these concerns are objective this study demonstrates that firms can reap the dividends of supply chain stability from blockchain application. In a context where external environmental uncertainty is rising significantly stable configuration is a key pathway to enhancing supply chain resilience. Therefore this study encourages firms to actively embrace blockchain technology to reduce operational volatility.

However firms should recognize that the empowering effect of blockchain is not fully released in all contexts. Specifically the research shows that firms facing higher environmental pressure those with stronger digital foundations and those lacking financing constraints gain more stabilization benefits from blockchain. Conversely this study reveals that firms with high financing constraints often fail to achieve significant effects due to a lack of resources for implementation even if they have a strong intent. Practitioners have also emphasized the capital shortages faced by SMEs in deploying underlying technologies . In summary to make more scientific digitalization decisions firms need to assess whether their own resources can support the deep integration of blockchain and focus on combining it with predictive tools like artificial intelligence.

On the other hand this study has direct implications for policymakers. Although blockchain can optimize supply chain structures the research also finds a resource threshold in this empowerment process. Therefore governments should take more precise measures. For example given the financing difficulties of SMEs governments should provide specialized financing support or interest subsidies for SME blockchain deployment to lower the threshold for digital transformation. Additionally governments should improve blockchain supply chain data standards to promote mutual recognition of information. Since blockchain benefits are critical under high economic policy uncertainty policy focus should shift toward building a consistent international legal framework to address institutional barriers in cross-border supply chain stability. In short the conditional nature of technology application implies that the policy focus should shift toward the overall optimization of the technological ecosystem.

This study has several limitations that provide opportunities for future research. First this study focuses on Chinese A-share listed firms which may limit the generalizability of the results to other types of companies. Compared to listed firms unlisted small and medium enterprises may have weaker motivation to adopt blockchain due to extreme resource scarcity and lower digital literacy. Also considering the differences in data sovereignty and legal frameworks across countries future research could conduct cross-country comparisons to investigate how blockchain effects vary in different institutional environments. Therefore future studies can explore other databases to examine the impact of blockchain on groups not covered in this study.

The heterogeneity evidence further indicates the stabilizing association is stronger in competitive markets and under high environmental uncertainty, suggesting blockchain's value depends on the market and environmental context of deployment. This is an interpretation that future research using within-market identification can test further.

Second there is room to improve the measurement method. This study uses text mining of annual reports to capture strategic intent. While this approach overcomes the difficulty of gathering large-scale data, it still has some weaknesses. Text disclosure often has time lags and may include impression management. This makes it hard to distinguish between basic technology development and actual application in business scenes. Future research could combine patent data smart contract frequency or survey data to build better indicators. This would help distinguish how different levels of blockchain adoption affect supply chain stability differently.

Third this study does not pay enough attention to the implementation process and dynamic evolution of blockchain. I focus on the outcomes after adoption rather than analyzing the motives and changes during the process (M. Wang et al., 2020). Digital transformation does not happen overnight. It is still a black box how firms overcome organizational inertia and collaboration complexity during technology integration. Future research could use case studies or longitudinal data to examine the full life cycle of blockchain applications. Researchers could also analyze the micro-mechanisms of supply chain stability at the contract level.

Fourth, the instrumental-variable specification does not absorb firm fixed effects and is thus not directly comparable in magnitude to the fixed-effects baseline; future work with instruments that vary within firm over time could reconcile the two.

Finally the measurement of firm risk or resilience may not be direct enough. Although I use supply chain volatility to reflect structural risk I did not capture short-term operational risks such as supply disruptions or logistics delays. The value of blockchain may appear more in real-time warnings and fast recovery during extreme shocks. Also even though I discussed the role of decentralization supply chain complexity is a broad concept. Differences in network structures like centralized versus mesh networks or changes in power dynamics may create complex effects. Future research should use technologies like digital twins to develop more direct resilience indicators. It should also explore the governance boundaries of blockchain under different network structures.

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Appendices

Appendix A. Variables and definition

Variable	Type	Definition and Measurement	Data Source
SCV_S	Dependent	Supplier-side supply chain volatility. Euclidean distance between the top-five supplier transaction-share vectors of two consecutive years; partners absent in one year are assigned a zero share. Higher values indicate greater partner turnover and lower stability.	CSMAR
SCV_C	Dependent	Customer-side supply chain volatility. Euclidean distance between the top-five customer transaction-share vectors of two consecutive years, constructed identically to SCV_S using customer sales shares.	CSMAR
ln_TFIDF_BC	Independent	Blockchain strategic disclosure intensity. Natural logarithm of one plus the TF-IDF weighted frequency of blockchain-related terms in the firm's MD&A section. Higher values indicate denser, more informative blockchain disclosure.	Firm annual reports (MD&A)
ln_BC_WordSum	Independent (robustness)	Alternative blockchain disclosure measure. Natural logarithm of the simple count of blockchain-related words in the MD&A section, used in place of the TF-IDF weighted index.	Firm annual reports (MD&A)
IV_Peer	Instrument component	Leave-one-out peer disclosure level. Average ln_TFIDF_BC of all other firms in the same city and the same industry in the same year (the focal firm's own value is excluded).	Firm annual reports; CSMAR
ln_BroadBandSubPort	Instrument component	Local broadband infrastructure. Natural logarithm of one plus the number of broadband access ports in the city where the firm is located in a given year.	Regional statistics
IV_Interact	Instrumental variable	Instrumental variable for blockchain disclosure intensity, defined as the interaction of the leave-one-out peer disclosure level and local broadband infrastructure (IV_Peer x ln_BroadBandSubPort).	Constructed (IV_Peer x ln_BroadBandSubPort)
Admin_Exp_Ratio	Mediating	Coordination / managerial efficiency channel. Total administrative expenses divided by total operating revenue.	CSMAR
SC_Concentration	Mediating	Supply chain concentration (structural-optimization channel). Aggregate transaction share of the top five suppliers and customers; entered in log form, so values may be negative. Lower values indicate a more diversified supply chain structure.	CSMAR

Variable	Type	Definition and Measurement	Data Source
ROA	Control	Profitability. Net profit divided by total assets.	CSMAR
Lev	Control	Financial leverage. Total liabilities divided by total assets.	CSMAR
Growth	Control	Revenue growth. Year-on-year growth rate of operating revenue.	CSMAR
Top1	Control	Ownership concentration. Shareholding percentage of the largest shareholder.	CSMAR
SOE	Control	State-owned enterprise status. Binary indicator equal to one for firms ultimately controlled by the state, and zero otherwise.	CSMAR
Size	Control	Firm size. Natural logarithm of total assets.	CSMAR
Age	Control	Firm age. Number of years since the firm's establishment.	CSMAR
CashFlow	Control (robustness)	Cash flow. Net operating cash flow scaled by total assets, included as an additional control in the alternative-controls robustness check.	CSMAR
Board_Size	Control (robustness)	Board size. Number of directors on the board, included as an additional control in the alternative-controls robustness check.	CSMAR
EPU_High	Heterogeneity	Policy uncertainty subsample indicator. Equals one for firm-years in which the annual mean of the China Economic Policy Uncertainty index is above the sample median.	China EPU Index
Is_Foreign_Oriented	Heterogeneity	Geopolitical-risk / foreign-orientation indicator. Binary variable equal to one for firms reporting positive overseas operating revenue.	CSMAR
HHI_Low	Heterogeneity	Market competition indicator. Equals one when the industry-year Herfindahl-Hirschman Index (sum of squared firm revenue shares within an industry-year) is below the median, indicating a more competitive market.	CSMAR (computed)
FC_High	Heterogeneity	Financing constraint indicator. Binary variable equal to one for firms with below-median scaled free cash flow.	CSMAR (computed)

Variable	Type	Definition and Measurement	Data Source
Dig_High	Heterogeneity	Digital foundation indicator. Equals one for firms with above-median digital infrastructure.	Firm annual reports / CSMAR
AI_High	Heterogeneity	Artificial intelligence integration indicator. Equals one for firms with above-median use of artificial intelligence.	Firm annual reports / CSMAR

Appendix B. Robustness Check: Alternative Measure of Independent Variable

Variables	Panel A: Baseline		Panel B: Replace X	
Variables	(1)SCV_S	(2)SCV_C	(3)SCV_S	(4)SCV_C
ln_TFIDF_BC	-0.0411***	-0.0320**	—	—
	(-3.310)	(-2.563)		
ln_BC_WordSum	—	—	-0.0148*	-0.0083
			(-1.690)	(-0.981)
ROA	0.1609***	0.1357**	0.1566***	0.1328**
	(3.208)	(2.321)	(3.122)	(2.273)
Lev	-0.1037**	-0.0984**	-0.1052**	-0.0995**
	(-2.472)	(-2.090)	(-2.506)	(-2.115)
Growth	0.0132**	0.0133*	0.0130**	0.0132*
	(2.185)	(1.806)	(2.152)	(1.786)
Top1	-0.0008	-0.0012*	-0.0009	-0.0012*
	(-1.273)	(-1.714)	(-1.328)	(-1.743)
SOE	0.0585**	0.0201	0.0575**	0.0195
	(2.577)	(0.897)	(2.544)	(0.873)
Observations	8948	8948	8948	8948
R-squared	0.3228	0.3149	0.3226	0.3147
Firm Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

*Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Unstandardized coefficients are reported. t-statistics are in parentheses.*

Appendix C. Robustness Check: Alternative Fixed Effects and Additional Controls

Variables	Panel C: Industry FE		Panel D: Add Controls	
Variables	(5)SCV_S	(6)SCV_C	(7)SCV_S	(8)SCV_C
ln_TFIDF_BC	-0.0086	-0.0081	-0.0386***	-0.0295**
	(-0.531)	(-0.614)	(-3.279)	(-2.351)
ln_BC_WordSum	—	—	—	—
ROA	-0.0299	-0.1165**	0.2152***	0.1905***
	(-0.735)	(-2.573)	(4.233)	(3.416)
Lev	-0.1188***	-0.0977***	-0.0477	-0.0445
	(-6.464)	(-5.243)	(-1.096)	(-0.952)
Growth	0.0223***	0.0378***	0.0118*	0.0121
	(4.777)	(6.450)	(1.953)	(1.644)
Top1	-0.0006**	-0.0003	-0.0012*	-0.0016**
	(-2.493)	(-1.296)	(-1.673)	(-2.114)
SOE	-0.0461***	-0.0471***	0.0490**	0.0126
	(-6.282)	(-6.632)	(2.144)	(0.591)
Size	—	—	-0.0594***	-0.0579***
			(-5.576)	(-4.604)
Age	—	—	0.0380**	0.0733***
			(2.473)	(3.136)
Observations	8948	8948	8948	8948
R-squared	0.0707	0.0758	0.3299	0.3242
Firm Fixed Effects	No	No	Yes	Yes
Industry Fixed Effects	Yes	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

*Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Unstandardized coefficients are reported. t-statistics are in parentheses.*

Appendix D. Robustness Check:Alternative Controls and Double-Clustered Standard Errors

Variables	Panel E: Alt Controls		Panel F: Double Cluster	
Variables	(9)SCV_S	(10)SCV_C	(11)SCV_S	(12)SCV_C
ln_TFIDF_BC	-0.0398***	-0.0307**	-0.0411*	-0.0320*
	(-3.166)	(-2.512)	(-2.202)	(-1.978)
ln_BC_WordSum	—	—	—	—
ROA	—	—	0.1609**	0.1357*
			(2.383)	(1.897)
Lev	-0.1352***	-0.1237***	-0.1037	-0.0984
	(-3.457)	(-2.896)	(-1.762)	(-1.623)
Growth	0.0142**	0.0143*	0.0132*	0.0133*
	(2.358)	(1.931)	(2.019)	(2.343)
Top1	-0.0006	-0.0010	-0.0008	-0.0012*
	(-0.959)	(-1.485)	(-1.271)	(-1.959)
SOE	0.0552**	0.0172	0.0585*	0.0201
	(2.450)	(0.771)	(2.093)	(0.885)
CashFlow	-0.0000	-0.0000	—	—
	(-0.000)	(-1.314)		
Board_Size	0.0070**	0.0060*	—	—
	(2.048)	(1.714)		
Observations	8947	8947	8948	8948
R-squared	0.3225	0.3145	0.3228	0.3149
Firm Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm & Year	Firm & Year

*Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Unstandardized coefficients are reported. t-statistics are in parentheses.*

Appendix E. Bootstrap Test Results for Mechanism

Channel	Indirect Effect	95% CI Lower	95% CI Upper	p-value
Blockchain → Admin Expense → SCV_S	-0.0016**	-0.0033	-0.0004	0.0036
Blockchain → SC Concentration → SCV_S	-0.0042**	-0.0081	-0.0008	0.0144
Blockchain → Admin Expense → SCV_C	-0.0016**	-0.0035	-0.0003	0.0144
Blockchain → SC Concentration → SCV_C	-0.0053**	-0.0100	-0.0010	0.0200

*Notes: Non-parametric bootstrap with 5,000 replications; percentile confidence intervals. All underlying models include firm and year fixed effects. Estimates are descriptive channel decompositions under a fixed-effects design and are not formally identified causal mediation effects. ** p < 0.05.*