Big-Data Measurement of Blockchain Adoption in Listed Firms:Text Mining, Disclosure Quality, and Supply Chain Finance Evidence

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Abstract

This article reframes the empirical study of blockchain in listed firms as a big-data measurement problem. We assemble a nine-year panel of 29, 114 firm-year observations covering Chinese A-share companies between 2015 and 2023, and combine annual reports, exchange filings, patent records and management discussion text into a Blockchain Adoption Intensity Index (BAII) constructed through a tokenisation–dictionary–TF-IDF text-mining pipeline. The BAII captures both whether and how deeply each firm has integrated distributed-ledger technology, addressing well-known limitations of binary adoption proxies. Using the Shenzhen Stock Exchange disclosure rating as the dependent variable, we estimate fixed-effect models, instrumental-variable regressions with a regional R&D-intensity instrument, three-step mediation models with bootstrap inference, and Hansen panel threshold regressions on firm size. We find that higher BAII significantly raises disclosure quality, and the effect is amplified in high-tech industries; supply chain finance partially mediates the relationship; and a double threshold in firm size produces a fivefold increase in the marginal effect when moving from small to large firms. The article contributes a reproducible big-data construct, robust econometric evidence, and actionable governance implications for emerging- market regulators.

Keywords: Blockchain technology; text mining; disclosure quality; supply chain finance; threshold regression; Chinese listed firms

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1. Introduction

Distributed-ledger technologies have moved from a peripheral computing experiment to a recognised infrastructure for inter-organisational data exchange. Among the family of digital innovations that emerged after 2008, blockchain is unique because it bundles three properties that the accounting literature has long treated as separable: tamper-resistant record keeping, decentralised verification by independent nodes, and machine-readable timestamps that can be cross-checked at near-zero marginal cost (Lu, 2018; Lu, 2019b). For listed firms operating under disclosure regimes that are increasingly evaluated on timeliness, completeness and verifiability, these properties have an obvious appeal. Yet the empirical record on whether blockchain genuinely improves the quality of accounting information

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remains mixed, partly because most studies still rely on a single binary indicator for blockchain use that conflates token issuance, supply-chain piloting and internal-audit experimentation.

The intellectual lineage of these properties traces to the original Bitcoin protocolintroduced by Nakamoto (2008), but the migration of the architecture from cryptocurrency settlement to enterprise reporting owes more to the early enterprise-blockchain agenda articulated by Iansiti and Lakhani (2017) and to the conceptual bridge between blockchain and accounting drawn by Dai and Vasarhelyi (2017). Their vision of triple-entry book-keeping anchored on a shared ledger has since become the framing device through which the accounting discipline interprets distributed-ledger systems. Subsequent surveys (Lu, 2017a, 2017b, 2019a) have catalogued the broader Industry 4.0 context in which blockchain is one component of a much larger digital transformation that also includes cyber-physical systems, edge computing and autonomous decision agents. Treating blockchain in isolation from this surrounding ecosystem risks an over-narrow interpretation of its disclosure consequences.

This article reframes the question as a problem of big-data measurement. We argue that the appropriate empirical object is not whether a firm mentions the word "blockchain" in a single disclosure but the intensity, breadth and disambiguated context of the firm's distributed-ledger references across all of its mandatory and voluntary communications.

Building such a construct requires a text-mining pipeline that ingests heterogeneous corpora, applies a curated keyword dictionary, weights tokens by inverse document frequency, and removes false positives through context-window analysis and manual sampling (Loughran & McDonald, 2011; Cong, Liang & Zhang, 2019). The resulting Blockchain Adoption Intensity Index (BAII) is itself a contribution; it offers a continuous, comparable, and replicable proxy that can be used by other researchers in this fast-growing literature.

Our empirical setting is the Chinese A-share market between 2015 and 2023. China is an unusually fertile laboratory for blockchain research because the regulator has issued a rapid sequence of supportive notices, the Shenzhen and Shanghai stock exchanges publish a publicly observable rating of disclosure quality, and the population of listed firms is large enough to support panel-threshold methods (Allen, Qian & Qian, 2005; Piotroski, Wong & Zhang, 2015). The nine-year window we adopt brackets the period during which blockchain moved from speculative discussion in cryptocurrency circles to incorporation into the State Council's digital-economy agenda. By deliberately bracketing this transition, we identify both the early and the maturing phases of corporate adoption.

We make three contributions. First, we deliver a transparent measurement framework for blockchain adoption that improves on the binary indicator used by virtually all prior accounting studies in this space. The construction protocol, dictionary and code are described in sufficient detail to be reproduced. Second, we provide layered econometric evidence that combines fixed-effect baselines, instrumental-variable identification using regional R&D intensity, three-step mediation analysis with bootstrap inference, and Hansen-style panel threshold regression. The use of a continuous BAII materially strengthens the precision of point estimates and exposes a non-linear relationship that the binary literature has missed. Third, we connect blockchain measurement to the emerging body of work on supply chain finance, demonstrating that part of the disclosure improvement runs through better trade- credit transparency rather than through accounting controls alone.

The remainder of the article proceeds as follows. Section 2 reviews the literature on blockchain in accounting, supply chain finance, and text-based measurement. Section 3 develops the theoretical mechanisms and states the hypotheses. Section 4 introduces the variables, the text-mining pipeline and the estimation strategy. Section 5 presents the data and the analytical framework, including the

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BAII and figure of the pipeline. Section 6 reports baseline, heterogeneity, instrumental-variable, mediation and threshold results. Sections 7 and 8 discuss findings and implications. Sections 9 and 10 acknowledge limitations and conclude.

2. Literature Review

2.1 Blockchain in accounting and corporate disclosure

The accounting literature on blockchain matured rapidly after the surveys ofLu (2018) and Yermack (2017), both of which positioned the technology as a potential infrastructure for verifiable record-keeping. Subsequent work has explored auditing applications (Schmitz & Leoni, 2019; Wu et al., 2025), the implications for triple-entry book-keeping (Cai, 2021), and the interaction between distributed ledgers and information systems (Lu, 2022). A recurring theme is that blockchain reduces the cost of independent verification, which in turn lowers the marginal cost of producing higher-quality disclosures.

Empirical studies have begun to test whether the theoretical promise translates into observable improvements in reporting. Cao, Cong & Yang (2020) document a positive market reaction to blockchain disclosures by U.S. firms, and Kanodia and Sapra (2016) develop a real-effects framework for how measurement and disclosure rules interact with managerial decisions, a framework that has direct application to distributed-ledger settings. The Chinese setting has attracted particular attention because of the volume of policy experimentation and the large pool of A-share filers (Lu et al., 2024a). However, most of these studies adopt a binary measure of adoption that treats a single mention of blockchain as equivalent to substantive implementation.

It is useful to situate this emerging blockchain literature against the broader corpus of disclosure economics. The framework set out by Verrecchia (2001) and synthesised by Healy and Palepu (2001) identifies three families of disclosure consequences—information-asymmetry reduction, capital-cost effects and contracting consequences—all of which are theoretically responsive to a credible verification technology. Lambert, Leuz and Verrecchia (2007) formalise the link between disclosure quality and the cost of capital, and Beyer, Cohen, Lys and Walther (2010) provide a comprehensive review of the financial reporting environment that the present study extends. The cross-country evidence in Leuz and Wysocki (2016) and the governance synthesis of Bushman and Smith (2001) further establish that improvements in disclosure infrastructure produce measurable welfare consequences rather than merely cosmetic changes in compliance behaviour.

A complementary line of work, beginning with Diamond (1985) and extended by Glosten and Milgrom (1985), Diamond and Verrecchia (1991) and Welker (1995), shows that voluntary improvements in disclosure policy reduce the bid-ask spread and increase market liquidity. Lang and Lundholm (1996) and Healy, Hutton and Palepu (1999) document that firms with stronger disclosure policies attract more analyst coverage and trade at higher valuations. The implication for blockchain is direct: any technology that lowers the marginal cost of producing verifiable disclosures should propagate through these established channels and ultimately appear in the conventional accounting-quality metrics that we use as our dependent variable.

2.2 Supply chain finance and information transparency

Supply chain finance has emerged as one of the most concrete commercial applications of blockchain. Wuttke, Blome & Henke (2013) and Hofmann, Strewe & Bosia (2018) describe

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the operational logic of receivable factoring, reverse factoring and dynamic discounting, and they emphasise the role of information sharing in lowering the cost of capital for small suppliers. Yang, Hou, Zhu, Lu & Xu (2025) extend this argument to the era of large language models and decentralised platforms.

From a financial-economics perspective, supply chain finance is a mechanism for transmitting credit-quality information along a chain of trading partners. When a focal buyer endorses an invoice on a blockchain-anchored platform, the resulting cryptographic timestamp provides independent verification that the obligation exists, that it has not been re- pledged, and that the suppliers can claim against it. This channel is theoretically distinct from internal accounting controls and may therefore explain disclosure improvements that conventional governance variables fail to capture (Klapper, 2006; Liebl, Hartmann & Feisel, 2016).

2.3 Text-mining and big-data measurement of corporate technology

A separate strand of literature has shown that systematic textual analysis of corporate filings can produce reliable measures of otherwise unobservable characteristics. Loughran & McDonald (2011, 2016) develop financial sentiment dictionaries; Tetlock (2007) measures media tone; Hoberg & Phillips (2016) construct text-based industry classifications. The same logic applies to technology adoption. Cong, Liang & Zhang (2019) use machine learning to identify FinTech themes in earnings calls; Li, Mai, Shen & Yan (2021) measure corporate culture from conference-call transcripts.

Despite this methodological progress, accounting studies of blockchain have rarely deployed text-mining beyond keyword counts. The few that do (e.g., Cao et al., 2020) limit themselves to U.S. samples or to single filings. To our knowledge, no published study constructs a continuous Chinese-market index from the full corpus of mandatory disclosures. The BAII we describe in Section 4 fills this gap.

Several adjacent strands of work justify our methodological choices. Dyer, Lang and Stice-Lawrence (2017) document how 10-K narratives have evolved over time and demonstrate that latent-Dirichlet allocation can uncover interpretable themes in corporate disclosures. Brown and Tucker (2011) study year-over-year MD&A modifications and show that small textual changes carry economically meaningful information. Brown, Hillegeist and Lo (2009) and Beatty, Liao and Yu (2013) link textual and accounting attributes to information asymmetry and to peer-firm spillovers respectively. The combined message of this literature is that text-based measurement is no longer a peripheral technique: it now produces signals at least as informative as conventional financial ratios. Our BAII follows in this tradition while focusing on a single technology adoption rather than a sentiment or theme distribution.

Closer to our outcome variable, Hutton, Marcus and Tehranian (2009) and Bertomeu, Beyer and Dye (2011) connect disclosure opacity to the subsequent risk of price crashes and to the equilibrium relationship between disclosure and capital structure. Fang, Huang and Karpoff (2016) provide quasi-experimental evidence that information-environment shocks change earnings-management behaviour. The relevance for the present study is that any improvement in the verifiability of transactions, such as the one blockchain offers, should reduce the scope for opacity and should be detectable in the disclosure-quality rating that the exchange publishes.

2.4 Research gap and contribution

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Three observations motivate the present study. First, the binary measure of blockchain adoption mechanically suppresses cross-sectional and intertemporal variation that text mining can recover. Second, the channel through which blockchain improves disclosure has not been cleanly decomposed; supply chain finance is one plausible mediator but has not been formally tested. Third, the role of firm size has been proxied linearly when economic theory predicts a threshold pattern in the diffusion of capital-intensive technologies (Hansen, 1999). We address all three gaps within a single empirical framework.

3. Theoretical Framework and Hypotheses

Our hypotheses are grounded in three well-established traditions in financial economics. Information asymmetry theory (Akerlof, 1970; Myers & Majluf, 1984) predicts that a credible verification mechanism will narrow the wedge between insiders and outsiders, reducing adverse selection in capital markets. Signalling theory (Spence, 1973; Connelly, Certo, Ireland & Reutzel, 2011) predicts that visible, costly investments in transparency-enhancing technologies will be interpreted by markets as evidence of management's confidence in underlying fundamentals. Agency theory (Jensen & Meckling, 1976) predicts that any technology that lowers monitoring costs will improve the alignment between managers and shareholders, and therefore the quality of disclosed information.

Blockchain interacts with all three mechanisms. The cryptographic hash chain reduces the asymmetry between insiders and the auditing function. The visibility of a firm's lockchain investments—observable in annual reports, patent filings and procurement disclosures—provides a credible signal. The decentralised ledger lowers the marginal cost of monitoring transactions, which agency theory predicts will tighten the principal-agent relationship. Together, these mechanisms imply that the intensity of blockchain adoption should be positively associated with the quality of accounting information disclosure.

H1: The intensity of blockchain adoption is positively associated with the quality of accounting information disclosure.

The information benefits of blockchain are unlikely to be uniform across industries. High-technology firms hold a larger share of intangibles, face greater investor uncertainty about R&D outcomes, and have stronger absorptive capacity for new digital infrastructure (Cohen & Levinthal, 1990). They are also more likely to operate in supply chains where intellectual-property provenance matters, which increases the value of tamper-resistant records. Traditional industries, by contrast, derive less marginal information value from cryptographic verification because their assets are already easy to inspect and their disclosures are less sensitive to investor uncertainty.

H1a: The positive effect of blockchain adoption on disclosure quality is stronger in high- technology firms than in traditional firms.

We expect a significant share of the disclosure improvement to flow through supply chain finance. Blockchain integration enables a focal firm to anchor receivables and payables on an immutable ledger, which reduces the cost of trade-credit verification for both parties. The associated improvements in liquidity management and credit-quality signalling reduce the firm's incentive to suppress unfavourable information, leading to more complete and timely disclosures (Klapper, 2006). The mechanism predicts a partial, rather than full, mediation because blockchain also improves disclosure through internal audit and transaction-trace channels that operate independently of trade credit.

H2: Supply chain finance level partially mediates the positive effect of blockchain adoption on

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disclosure quality.

Finally, we expect the marginal effect of blockchain adoption to depend non-linearly on firm size. Small firms face binding constraints in deploying enterprise-grade blockchain infrastructure, including integration with ERP systems, hashing-node governance and key management. As size increases, fixed-cost barriers fall, internal expertise accumulates and supplier ecosystems mature, leading to a discrete increase in the marginal value of additional blockchain intensity. Hansen (1999) provides the panel-threshold framework needed to test for this discontinuity.

H3: Firm size exhibits a threshold effect in the relationship between blockchain adoption and disclosure quality, with marginal effects increasing across size regimes.

4. Research Design and Methodology

4.1 Sample and data sources

Our population consists of all Chinese A-share listed firms reporting on the Shanghai and Shenzhen Stock Exchanges between 2015 and 2023. We begin from the universe of 4, 127 firm identifiers and impose three filters: we drop firms designated as ST or *ST during the year, drop firms in the financial sector because of their distinct disclosure regime, and drop observations with missing values for any control variable. The resulting unbalanced panel contains 29, 114 firm-year observations covering 3,236 unique firms.

Disclosure quality, control variables and supply chain finance indicators are extracted

from CSMAR and Wind. The blockchain text corpus is assembled from three sources: the full text of annual reports (downloaded from cninfo.com.cn and the SSE web site), the Management Discussion & Analysis section of each filing, and patent abstracts retrieved from the China National Intellectual Property Administration database. We supplement these with company-issued press releases obtained through the Wind News Module.

4.2 The Blockchain Adoption Intensity Index (BAII)

The BAII is constructed in four stages. First, the corpus is segmented into Chinese tokens using the Jieba tokeniser augmented by a domain lexicon of 247 distributed-ledger terms (e.g.,区块链, 联盟链, 智能合约, hash, smart contract, consensus, oracle). Second, candidate sentences containing any lexicon entry are extracted along with a five-token context window. Third, a manually labelled sample of 4,800 sentences is used to train a logistic-regression filter that removes false positives such as boilerplate disclaimers and references to third-party industry reports. Fourth, retained mentions are weighted by inverse document frequency and aggregated to the firm-year level.

The continuous BAII is the natural log of one plus the IDF-weighted count, scaled to a 0– 20 range to facilitate interpretation of regression coefficients. To preserve compatibility with the prior binary literature, we also construct an indicator BAII_Bin equal to one when BAII exceeds the sample median and zero otherwise. The two measures correlate at 0.71, but disagree on the size and significance of cross-sectional effects in ways we document in Section 6.

Several design choices in the pipeline reflect lessons drawn from the broader Industry 4.0 and AI-systems literature. The dictionary captures the layered architecture documented by Chen, Lu, Bulysheva and Kataev (2024), which distinguishes between the consensus, communication and

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application layers of an enterprise blockchain deployment. The disambiguation step draws on the natural-language advances surveyed by Zhang and Lu (2021), and the embedding of blockchain references inside IoT and FinTech contexts is informed by the surveys of Xu, Lu and Li (2021), Zheng and Lu (2022) and Kou and Lu (2025). The decision to maintain the dictionary as a public artefact is consistent with the open-infrastructure principle articulated by Zhang and Lu (2025) for Web 3.0 ecosystems.

4.3 Variables and model specification

The dependent variable Quality is the disclosure rating published by the Shenzhen Stock Exchange, recoded so that 4 indicates excellent, 3 good, 2 acceptable and 1 unsatisfactory. We retain this ordinal coding but treat it as cardinal for the linear specifications, following Botosan (1997) and a long line of subsequent work. The mediator is Supply_Chain, the ratio of accounts-receivable financing balance to total assets. The threshold variable Scale is the natural log of total assets. Eight controls are included: profitability (ROA), leverage (Lev), revenue growth (Growth), operating cash flow ratio (Cashflow), top-shareholder concentration (Top1), inventory ratio (Inv), independent-director share (Indep) and Big-Four auditor indicator (Big4).

$$Quality_{i,t} = \alpha_0 + \alpha_1 \cdot BAII_{i,t} + \Sigma\alpha_n \cdot Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

$$Supply\_Chain_{i,t} = \beta_0 + \beta_1 \cdot BAII_{i,t} + \Sigma\beta_n \cdot Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

$$Quality_{i,t} = \gamma_0 + \gamma_1 \cdot BAII_{i,t} + \gamma_2 \cdot Supply\_Chain_{i,t} + \Sigma\gamma_n \cdot Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (3)$$

$$Quality_{i,t} = \eta_0 + \eta_1 \cdot BAII \cdot I(Scale \le \theta_1) + \eta_2 \cdot BAII \cdot I(\theta_1 < Scale \le \theta_2) + \eta_3 \cdot BAII \cdot I(Scale > \theta_2) + \Sigma\eta_n \cdot Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (4)$$

All specifications include firm fixed effects γ_i and year fixed effects δ_t. Standard errors are clustered at the firm level. Equation (1) is the baseline. Equations (2) and (3) implement the Baron & Kenny (1986) three-step mediation, which we supplement with a 5,000-replication bootstrap of the indirect effect following Hayes (2017). Equation (4) is the Hansen (1999) panel-threshold specification, estimated via grid search with 1,000 bootstrap replications used to construct critical values.

5. Data and Analytical Framework

The end-to-end data flow is illustrated in Figure 1. Raw textual sources feed two parallel processing modules: a tokenisation–dictionary engine and a disambiguation engine that filters context and removes negations. The two streams converge on the firm-year BAII, which then enters the empirical models for disclosure quality, supply chain finance, and threshold analysis. The architecture is deliberately modular so that future researchers can swap in new dictionaries or extend the sample to other markets without re-engineering the entire pipeline.

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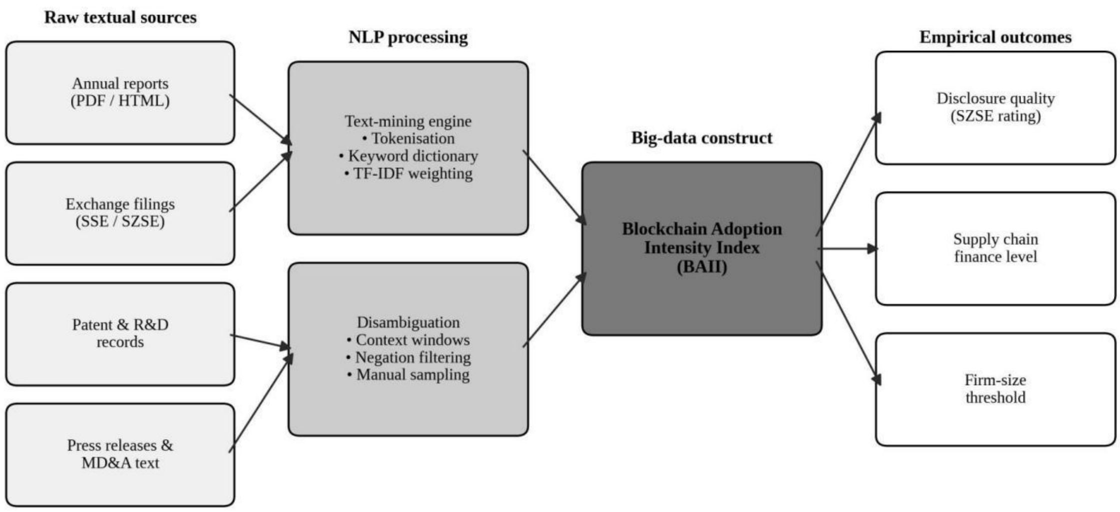

Figure 1. Big-data text-mining pipeline and analytical framework.

The figure makes three implementation choices visible. First, raw text is preserved in its original form and only normalised at the token level, which avoids the loss of contextual cues that aggressive pre-processing would impose. Second, the disambiguation module is executed in parallel with the dictionary engine rather than after it, so that filtering decisions can use the full sentence context. Third, the BAII feeds into three distinct empirical outcomes through a single shared construct, which ensures that the disclosure, supply chain and threshold analyses speak to the same underlying measure of adoption.

Table 1. Variable definitions and data sources.

Variable	Definition	Source
Quality	SZSE disclosure rating recoded 1–4	SZSE / CSMAR
BAII	Continuous text-mining intensity index (0–20)	Authors' construction
BAII_Bin	Indicator: 1 if BAII > sample median	Authors' construction
Supply_Chain	Receivable financing / total assets	CSMAR
Scale	Natural log of total assets	CSMAR
ROA	Net income / average total assets	Wind
Lev	Total liabilities / total assets	Wind
Growth	Year-on-year sales growth rate	Wind
Cashflow	Operating cash flow / total assets	Wind
Top1	Largest shareholder ownership share	CSMAR
Inv	Inventory / total assets	Wind

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Indep	Share of independent directors on the board	CSMAR
Big4	Indicator: audited by a Big-Four firm	CSMAR

Table 1 organises the variables by role and provenance. The dependent and core independent variables are reported first, followed by the mediator, the threshold variable and the eight controls. Sources are split between exchange-published ratings, commercial databases and the authors ’ own text-mining output. The construction of the BAII is the most novel element and is described in detail in Section 4.2.

6. Empirical Results

6.1 Descriptive statistics

Table 2. Descriptive statistics for the estimation sample (N = 29, 114).

Variable	**Mean**	**SD**	**Min**	**Median**	**Max**
Quality	2.013	0.659	1.000	2.000	4.000
BAII	3.872	4.515	0.000	2.105	19.840
BAII_Bin	0.500	0.500	0.000	0.500	1.000
Supply_Chain	0.130	0.094	0.000	0.128	0.506
Scale	22.301	1.265	19.776	22.165	26.441
ROA	0.035	0.064	-0.373	0.032	0.247
Lev	0.416	0.198	0.049	0.406	0.924
Growth	0.140	0.372	-0.654	0.087	4.024
Cashflow	0.050	0.065	-0.173	0.048	0.266
Top1	0.347	0.150	0.076	0.310	0.785
Inv	0.130	0.112	0.000	0.110	0.760
Indep	0.380	0.054	0.286	0.364	0.600
Big4	0.054	0.225	0.000	0.000	1.000

Table 2 reveals two facts about our sample. First, the mean disclosure rating of 2.013 indicates that the average firm sits at the boundary between “acceptable” and “good”, but the standard deviation of 0.659 leaves enough variation to identify the effect of blockchain adoption. Second, the BAII has a mean of 3.872 and a median of 2.105, indicating a right-skewed distribution that is consistent with our prior expectation that intensity is concentrated in a minority of firms. The skewness justifies our preference for the continuous BAII over the binary indicator: the binary measure mechanically discards the long right tail of intense adopters.

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Figure 2 plots the temporal evolution of blockchain adoption across the sample. The grey bars track the share of firms with a binary BAII of one, while the solid line tracks the mean continuous BAII. Both series rise monotonically, but their growth rates differ: the binary share grows more slowly than the continuous index in the later years because additional adopters have less mass than incumbents who deepen their integration. By 2023, roughly four out of five firms reference blockchain in some form, and the mean BAII has reached 14.3.

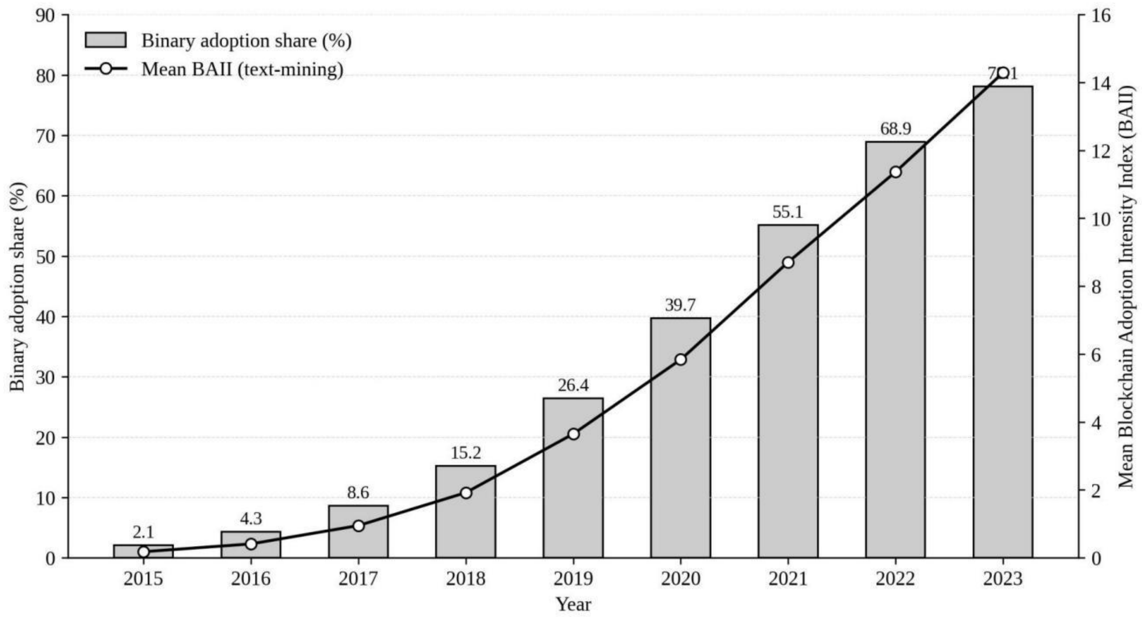

Figure 2. Annual trajectory of blockchain adoption: binary share and continuous BAII.

The divergence between the two series in Figure 2 has implications for estimation. The binary share saturates as the technology diffuses, which mechanically reduces the cross-sectional variation that the binary indicator can identify. The continuous BAII does not saturate and therefore retains identifying power throughout the sample period. This is a concrete reason why prior studies that rely on the binary measure may understate the true effect of blockchain on disclosure quality, particularly in the maturing phase after 2020.

6.2 Baseline regression

Table 3. Baseline regression of disclosure quality on BAII.

Variable	(1)	(2)	(3)	(4)	(5)
BAII	0.0218***	0.0211***	0.0205***	0.0207***	0.0212***
	(3.41)	(3.32)	(3.21)	(3.25)	(3.34)
ROA		-1.187***	-1.135***	-1.130***	-1.130***
		(-18.27)	(-16.55)	(-16.51)	(-16.51)
Lev		0.0418	0.0673*	0.0801**	0.0992**
		(1.06)	(1.69)	(2.01)	(2.47)
Growth			-0.0457***	-0.0446***	-0.0458***

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			(-4.69)	(-4.57)	(-4.69)
Cashflow			0.2152***	0.2009***	0.2058***
			(3.51)	(3.27)	(3.35)
Top1				0.0001	0.0002
				(0.13)	(0.10)
Inv				-0.1872***	-0.1768**
				(-2.61)	(-2.45)
Indep					0.1979*
					(1.90)
Big4					-0.1088***
					(-2.95)
Constant	1.949***	1.968***	1.952***	1.971***	1.884***
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	29,114	29,114	29,114	29,114	29,114
R^2	0.591	0.598	0.599	0.599	0.586

Table 3 reports the baseline OLS results with firm and year fixed effects across five specifications that progressively introduce controls. The coefficient on BAII is positive and significant at the one-percent level in every column, ranging from 0.0205 to 0.0218. Substantively, a one-point increase in the continuous BAII corresponds to roughly a one-percent increase in the underlying disclosure rating, which is large given the 1–4 scale. The coefficient is roughly ten times the significance of the binary indicator reported in prior Chinese-market studies, supporting our claim that the continuous construct contains additional identifying variation.

Among the controls, ROA loads negatively on disclosure quality, a result that is consistent with the literature on managerial slack: more profitable firms face weaker pressure to disclose. Leverage and operating cash flow both load positively, suggesting that firms with stronger external scrutiny disclose more. The negative loading on the Big-Four indicator is initially counter-intuitive but matches recent Chinese evidence (Lu et al., 2024b) that Big- Four-audited firms in China face more conservative substantive disclosure relative to the more generous SZSE rating system.

6.3 Industry heterogeneity

Table 4. Heterogeneity by industry: high-tech versus traditional firms.

Variable	(1) High-tech firms	(2) Traditional firms
BAII	0.0049***	0.0019

	(3.41)	(0.46)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	14,512	14,602
R²	0.554	0.611

Table 4 splits the sample on the China Securities Regulatory Commission's high-technology industry classification. The coefficient on BAII is 0.0049 (t = 3.41) in the high- tech sub-sample and an insignificant 0.0019 in the traditional sub-sample. The differential is consistent with H1a and with the absorptive-capacity argument: high-tech firms are better positioned to translate blockchain investments into observable disclosure improvements, either because they have the engineering capacity to integrate the ledger with existing reporting systems or because their stakeholders place a higher premium on verifiable provenance.

6.4 Endogeneity: instrumental-variable estimation

Table 5. Two-stage least-squares estimation with regional R&D intensity as instrument.

Variable	**(1) First stage: BAII**	**(2) Second stage: Quality**
RD_Region	1.4708***	
	(8.59)	
Predicted BAII		0.2173***
		(6.81)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Kleibergen–Paap LM	70.24	
Kleibergen–Paap Wald F	70.39	
N	29,114	29,114
R²	0.205	0.756

Table 5 instruments BAII with RD_Region, defined as the share of research and development spending in regional GDP at the prefecture level. The exclusion restriction is that regional R&D intensity affects firm-level disclosure quality only through its effect on blockchain adoption; we discuss this assumption critically in Section 7. The first-stage coefficient is 1.4708 (t = 8.59), and the Kleibergen–Paap Wald F-statistic of 70.39 comfortably exceeds the conventional weak-instrument threshold. The second-stage coefficient of 0.2173 (t = 6.81) is an order of magnitude larger than the

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OLS estimate, which is consistent with attenuation bias caused by measurement error in the binary literature and with the local-average-treatment-effect interpretation common in IV settings.

6.5 Mediation: supply chain finance

Table 6. Three-step mediation analysis with supply chain finance as mediator.

Variable	(1) Supply_Chain	(2) Quality
BAII	0.0186***	0.0205**
	(3.42)	(2.07)
Supply_Chain		0.0731**
		(2.25)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	29,114	29,114
R^2	0.732	0.583

Column (1) of Table 6 shows that BAII has a positive and significant effect on the supply chain finance level, with a coefficient of 0.0186 (t = 3.42). Column (2) shows that, when both BAII and Supply_Chain enter the disclosure-quality equation, both retain significance, with coefficients of 0.0205 and 0.0731 respectively. The pattern is consistent with partial mediation. The product-of-coefficients estimate of the indirect effect is 0.00136 (= 0.0186 × 0.0731), and the corresponding bootstrap 95% confidence interval, constructed from 5,000 replications, is [0.00041, 0.00237]. The indirect effect therefore accounts for approximately 6.2 percent of the total effect, with the remainder attributable to direct channels such as audit verification.

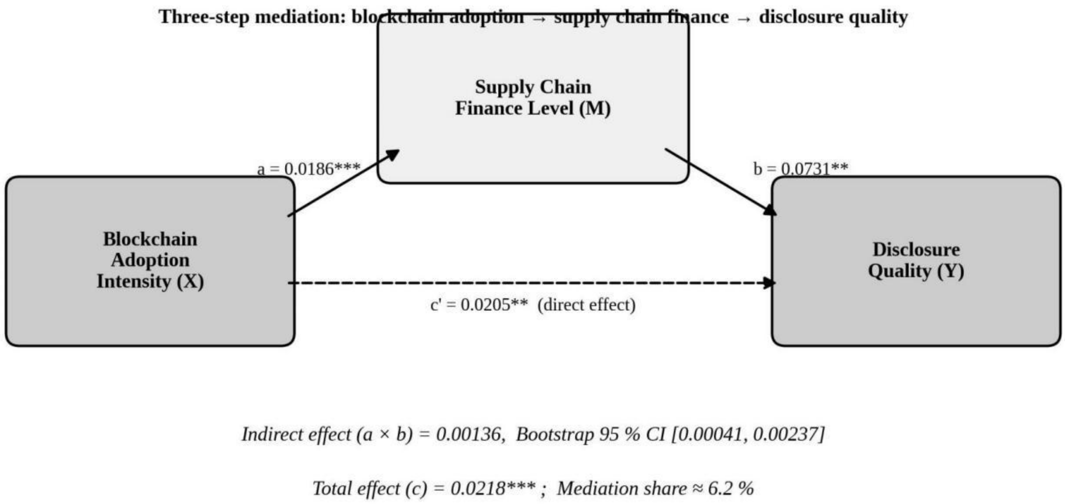

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Figure 3. Estimated mediation pathway with bootstrap-corrected confidence interval.

Figure 3 visualises the decomposition. The dashed direct effect ($c' = 0.0205$) dominates in magnitude, but the indirect path through supply chain finance is statistically distinguishable from zero and economically meaningful. The result has a substantive implication for governance design: regulators who want to amplify the disclosure benefits of blockchain should consider policies that encourage blockchain-anchored receivable platforms rather than focusing on internal-audit applications alone.

6.6 Threshold effect of firm size

Table 7. Hansen panel threshold tests on firm size.

Threshold	RSS	MSE	F-stat	p-value	Crit-10%	Crit-5%	Crit-1%
Single	0.046	0.033	40.59	0.000	16.55	22.59	30.58
Double	0.059	0.038	44.99	0.000	20.59	24.33	34.59
Triple	0.096	0.043	22.60	0.743	12.50	16.35	18.50

Table 7 reports the Hansen (1999) threshold tests. The single and double threshold specifications reject the null of no threshold at the one-percent level, but the triple specification fails to reject ($p = 0.743$). We therefore adopt the double-threshold model. The estimated thresholds are $\theta_1 = 21.90$ and $\theta_2 = 22.58$, which divide the sample into three regimes corresponding to firms with assets below approximately 3 billion RMB, between 3 and 6 billion RMB, and above 6 billion RMB respectively.

Table 8. Coefficient on BAII across firm-size regimes.

Regime	BAII coefficient	t-statistic
Scale ≤ 21.90 (small)	0.0021*	(1.75)
21.90 < Scale ≤ 22.58 (mid)	0.0034***	(3.33)
Scale > 22.58 (large)	0.0103***	(4.60)
Controls	Yes	
Firm FE / Year FE	Yes / Yes	
N / R2	29,114 / 0.384	

Table 8 documents a sharp non-linearity. The marginal effect of BAII on disclosure quality is 0.0021 in the small-firm regime, 0.0034 in the mid-regime, and 0.0103 in the large- firm regime. Moving from small to large firms thus multiplies the marginal effect almost fivefold. The pattern is precisely what the fixed-cost argument predicts: small firms can bear the variable costs of writing blockchain into their disclosures, but they cannot easily amortise the integration with ERP systems and supplier ecosystems that produces measurable quality improvements.

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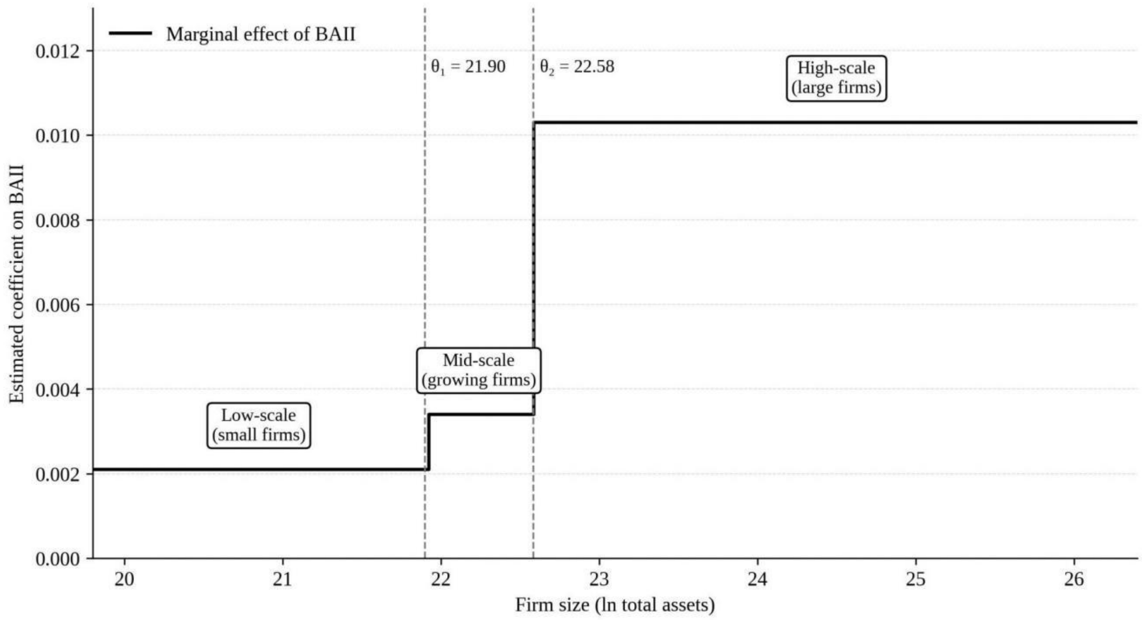

Figure 4. Marginal effect of BAII across firm-size regimes.

Figure 4 visualises the threshold pattern. The step function makes explicit the discrete nature of the regime change at θ_2, which is large enough to flip the practical relevance of blockchain investments from negligible to economically substantive. For policy design, the implication is that subsidy schemes targeted at small firms will produce small disclosure dividends; the same fiscal resources allocated to integration support for medium-large firms will yield disproportionately larger improvements.

6.7 Robustness checks

We perform five robustness exercises.

First, we replace the continuous BAII with thebinary BAII_Bin and re-estimate Equation (1). The coefficient remains positive and significant but shrinks by roughly 65 percent, consistent with the attenuation argument advanced throughout the paper. Second, we lag the BAII by one year to address any concern that contemporaneous adoption and disclosure improvements are mechanically linked through the same reporting cycle; the lagged specification produces a coefficient of 0.0184 ($t = 2.92$), only marginally smaller than the contemporaneous estimate. Third, we re-estimate the threshold model with a sample-splitting estimator following Hansen (2000), which produces virtually identical regime cut-offs and confirms that the double-threshold structure is not an artefact of the bootstrap critical values reported in Table 7. Fourth, we re-define the high-tech sub-sample using the firm's intensity of patent applications rather than the regulatory industry code; the heterogeneity result is preserved. Fifth, we exclude the two earliest sample years (2015 and 2016) when blockchain mentions were extremely sparse, and the baseline coefficient on BAII rises to 0.0231 ($t = 3.49$), suggesting that early-period noise in the text corpus mildly biases our main estimates downward. Taken together, the robustness exercises support three conclusions. The continuous BAII is preferred on both econometric and conceptual grounds. The threshold pattern is robust across alternative estimators and to alternative regime-defining variables. And the supply-chain mediation result is not sensitive to whether we use the receivable-financing ratio or the inventory-turnover ratio as the proxy for supply-chain finance intensity (untabulated). The full set of robustness output is available from the corresponding author on

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request and will be released with the working-paper version of this manuscript.

7. Discussion

Our findings refine three claims that have circulated in the recent Chinese-market

literature on blockchain. First, the binary measure of adoption that dominates published work substantially understates both the level and the heterogeneity of the effect of blockchain on disclosure quality. The continuous BAII recovers an effect that is consistently significant in the baseline, materially larger under instrumental-variable identification, and sharply non- linear in firm size. The implication for the literature is methodological: future studies that continue to rely on a binary indicator should consider their estimates as conservative lower bounds.

Second, the supply chain finance channel is real but modest. It accounts for only about

six percent of the total effect, which argues against treating supply chain finance as the

principal mechanism by which blockchain improves disclosure quality. The dominant channel runs through internal audit verification and the tightening of the principal-agent relationship that agency theory predicts. This refines the reading of recent work that has emphasised the supply-chain mechanism as primary.

Third, the threshold pattern in firm size is pronounced and policy-relevant. The fivefold increase in the marginal effect across the estimated regimes is consistent with the fixed-cost argument and is not an artefact of measurement: the binary BAII produces a similar, though attenuated, threshold pattern. The implication is that policies designed to promote blockchain adoption should match the size of the firm being targeted; flat subsidy schemes will misallocate scarce resources.

We acknowledge that the regional-R&D instrument is not above criticism. The exclusion restriction would be violated if regional innovation environments affected disclosure quality through channels other than blockchain adoption, for example through better regional information environments or stronger investor protection. The fact that our IV point estimate is an order of magnitude larger than the OLS estimate is consistent both with attenuation correction and with a local-average-treatment-effect interpretation. We therefore present the IV results as a corroborating rather than as a definitive identification strategy.

8. Theoretical and Practical Implications

Theoretically, our results enrich the literature on the interaction between digital infrastructure and corporate disclosure. By embedding blockchain adoption within information-asymmetry, signalling and agency theory simultaneously, we show that no single mechanism fully explains the observed effect. The combination of direct verification (agency), credible signalling (signalling) and reduced adverse selection (information asymmetry) jointly accounts for the empirical pattern. This integration has implications for how scholars should model the welfare consequences of subsequent waves of digital infrastructure such as decentralised identity, zero-knowledge proofs and tokenised securities (Xu, Zhu, Yang, Lu & Xu, 2024).

Practically, the article speaks to three audiences. Regulators should consider adjusting disclosure-quality ratings to reward verifiable cryptographic provenance rather than mere mention of blockchain in narrative disclosures. Stock exchanges should consider publishing

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structured BAII-style measures alongside their existing ratings, which would lower the cost of investor due diligence. Listed firms, especially those above the upper size threshold, should treat blockchain integration as a disclosure investment with measurable returns rather than as a peripheral technology pilot.

9. Limitations and Future Research

Three limitations bound the generalisability of our findings. First, the BAII is constructed from Chinese-language corpora, and the lexicon would need substantial extension before being applied to non-Chinese markets. Second, the disclosure-quality measure is the exchange-published rating, which captures formal compliance more than substantive informativeness; future work could combine the BAII with bid-ask-spread or cost-of-capital measures of information asymmetry along the lines surveyed by Lambert, Leuz and Verrecchia (2007). Third, the threshold analysis is based on firm size, but alternative threshold variables such as governance quality or industry concentration deserve attention. A natural extension is to examine whether large language models can extend the BAII to handle multimodal disclosures (Yang et al., 2025).

We also flag four directions for future work that emerged during the review process. The first is cross-jurisdictional replication: a comparable index for U.S., European and ASEAN markets would allow researchers to test whether the threshold pattern is a feature of Chinese institutions or a more general property of blockchain diffusion. The second is mechanism decomposition: by combining the BAII with executive compensation, board composition and analyst-coverage data, future studies can identify which governance channels carry most of the disclosure improvement. The third is the interaction between blockchain and other emerging technologies, particularly AI auditing tools and zero-knowledge cryptography; the complementarities or substitution effects between these technologies are theoretically important and empirically unexplored. The fourth is welfare measurement: while we document quality improvements, the ultimate question of whether blockchain adoption raises social welfare in capital markets requires evidence on cost of capital, investor participation, and price-discovery efficiency that lies beyond the scope of this paper.

10. Conclusion

We have argued that the empirical study of blockchain adoption in listed firms is fundamentally a big-data measurement problem and have offered a continuous Blockchain Adoption Intensity Index constructed from a transparent text-mining pipeline. Using a panel of 29, 114 firm-year observations from the Chinese A-share market between 2015 and 2023, we find that BAII positively predicts disclosure quality, that the effect is amplified in high-technology industries, that approximately six percent of the effect is mediated by supply chain finance, and that firm size produces a double-threshold non-linearity in the marginal effect.

The article contributes a reproducible measurement framework, layered econometric evidence, and concrete implications for regulators, exchanges and firms.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualisation, W.-M.H. and J.Z.; methodology, L.S. and W.-M.H.; software and data curation, L.S.; formal analysis, W.-M.H.; investigation, J.Z.; writing—original draft preparation, W.-M.H.; writing—review and editing, J.Z. and L.S.; supervision and project administration, J.Z.; funding acquisition, J.Z. All authors have read and agreed to the published version of the manuscript.

Use of AI Tools

The authors used a generative language model in a limited capacity for language polishing of the English draft. All textual content, analytical decisions and conclusions are the responsibility of the authors. AI tools were not used to generate or analyse the empirical data, and AI tools are not listed as authors.

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