Tokenized Account Receivables and Firm Growth in China[*]

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Abstract

We provide the first firm-level evidence that blockchain technology can spur growth in the real economy. Exploiting the staggered adoption of tokenized accounts receivable (TAR) by Chinese state-owned enterprises (SOEs) between 2015 and 2022, we link administrative records on RMB 14.80 billion of TAR transactions to the financial statements of 4,719 upstream suppliers. A doubling of TAR exposure is associated with a 9.6% increase in total assets, a 13.7% increase in liabilities, a 15.5% increase in main business income, and a 13.6% increase in tax payments, with no detectable change in return on equity. Consistent with a production-expansion mechanism, the gains are largest for firms closest to the issuing SOE and for firms whose customers are more liquidity-constrained or whose own supplier base is narrower. These patterns indicate that blockchain-enabled supply-chain finance generates substantial real effects by relaxing financing frictions deep within supplier networks.

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1 Introduction

Can blockchain technology adoption bring real economic benefits? Conceptually, distributed ledger technology can enhance transparency and transactional efficiency, there is no empirical evidence showing whether and how distributed ledger technology (DLT) can tangibly influence firm behavior and performance. This paper provides the first causal evidence that blockchain technology can spur firm growth through tokenized accounts receivables (TAR) enabled by DLT adoption in Chinese supply chain finance.

We provide the first firm-level evidence that blockchain can spur firm growth by alleviating collateral constraints. The setting for our investigation is China's industrial supply chain, where a fundamental credit mismatch persists. State-owned enterprises (SOEs), which execute the majority of large-scale infrastructure projects, enjoy abundant access to low-cost credit. However, their upstream suppliers—over 96 percent of which are small and medium-sized private enterprises (SMEs)—face severe financing constraints. These SMEs hold accounts receivable from creditworthy SOEs but cannot readily convert these claims into working capital, because financial institutions lack reliable mechanisms to verify the authenticity, ownership, and encumbrance status of such receivables. This friction constrains SME production capacity, which in turn limits the entire supply chain's output.

In 2015, a consortium of major SOEs launched Cloudchain Group, which introduced a tokenized accounts receivable (TAR) product. Built on a permissioned blockchain, TARs represent payment obligations from SOEs as digital tokens that can be cryptographically verified, split, transferred, and used as collateral. Critically, TARs circulate through the supply chain: a tier-1 supplier that receives a TAR from an SOE can use that same TAR to pay its own upstream suppliers, extending financing benefits deep into the supply chain while maintaining an immutable audit trail that mitigates the risk of duplicate financing.

We study the introduction of TARs across supply chains linked to ten major SOEs between 2015 and 2022. Our analysis combines two unique datasets: administrative transaction records from Cloudchain Group, covering 14,786 TAR transactions totaling RMB 14.80

billion, and comprehensive firm-level financial data from China's State Administration for Industry and Commerce, which allow us to track the performance of 13,309 firms over eight years. We exploit staggered SOE adoption of TARs as a plausibly exogenous shock to upstream SMEs, because adoption decisions were driven by SOE shareholder structure and central government policy priorities rather than by the characteristics of individual supplier firms.

Our empirical strategy constructs firm-year measures of TAR exposure, matches treated and control firms using propensity scores based on pre-treatment financial characteristics, and estimates treatment effects in a difference-in-differences framework. This design allows us to isolate the causal impact of TAR access on firm outcomes.

Three main findings emerge. First, TAR adoption benefits all firms in the supply chain. one percent increase in TAR exposure is associated with a 0.132 percent increase in assets, an 0.191 percent increase in liabilities, and a 0.215 percent increase in operating income. These gains reflect both a direct effect—TARs provide immediately pledgeable collateral—and an indirect effect: by reducing upstream suppliers' production risk, TARs enable downstream firms to expand output. Extrapolating our estimates, full tokenization of the core SOE groups' 2022 accounts-payable flow would raise their suppliers' assets, liabilities, operating income, and tax payments by 57.61, 93.15, 109.81, and 96.51 percent, respectively.

Second, the benefits are distributed asymmetrically, favoring downstream firms. This finding supports the hypothesis that the production expansion effect dominates the direct collateral effect. For each increase in TAR tier (moving closer to the downstream SOE), firms experience additional loss of 4.5 percent in assets, 7.7 percent in liabilities, and 0.4 percent in income. Downstream firms benefit more because the indirect effect amplifies as one moves toward the final demand shock.

Third, the magnitude of treatment effects varies predictably with supply chain characteristics. Firms with more liquidity-constrained customers capture larger gains from TAR

access, consistent with TARs substituting for constrained working capital. Conversely, firms with larger supplier bases experience smaller benefits, suggesting that coordination costs diminish the production expansion effect when supply chains become more complex.

Our paper makes three contributions. First, we provide the first empirical evidence that blockchain technology can generate real economic effects, moving beyond the literature's focus on technical feasibility or financial market applications. Second, we identify a specific mechanism—relaxation of credit constraints through tokenized receivables—by which distributed ledger technology can stimulate firm growth, contributing to the supply chain finance literature. Third, our findings inform policy debates about blockchain regulation and digital financial inclusion, particularly in developing economies where credit frictions are severe.

The remainder of the paper proceeds as follows. Section 2 develops a theoretical framework that generates testable hypotheses about the direct and indirect effects of TAR adoption. Section 3 describes the institutional background and our data. Section 4 presents the empirical strategy. Section 5 reports the main results. Section 6 discusses robustness checks and placebo tests. Section 7 concludes with policy implications and directions for future research.

Literature review

This paper contributes to three related strands of research. The first studies blockchain-based financial innovation and the economics of tokenization. Blockchain can reduce verification frictions in supply chains by making transactions, obligations, and counterparty histories more transparent (Dong, Qiu, and Xu, 2023; Chod et al., 2020; Wang and Xu, 2022; Chen et al., 2023; Cui, Gaur, and Liu, 2024). A related literature studies how permissioned blockchains are adopted and governed when the parties that bear adoption costs are not necessarily the parties that receive the largest benefits (Iyengar et al., 2023b,a). More broadly, work on token-based finance shows that tokens can affect financing capacity, adoption incentives, governance, moral hazard, and product-market competition (Cong, Li,

and Wang, 2021, 2022; Chod, Trichakis, and Yang, 2022; Gan, Tsoukalas, and Netessine, 2021; Chod and Lyandres, 2023). Recent empirical evidence also suggests that blockchain can improve financial inclusion when verifiable records relax information frictions (Jiang, Li, and Wang, 2026). The paper directly contributes to this literature by providing empirical evidence on blockchain's real economic impact, moving beyond technical feasibility studies.

The second strand studies trade credit, accounts receivable, and supply-chain finance. This literature explores how firms use trade credit as a short-term financing tool, the role of accounts receivable in easing liquidity constraints, and the frictions that prevent efficient receivable monetization (e.g., verification costs, double-spending risk, and lack of pledgeability). Classic theories view trade credit as a response to information asymmetry, credit rationing, collateral liquidation advantages, and relationship enforcement (Petersen and Rajan, 1997; Biais and Gollier, 1997; Burkart and Ellingsen, 2004; Cuñat, 2007; Fabbri and Menichini, 2010). Accounts receivable are therefore not only accounting claims, but also financing and monitoring instruments (Mian and Smith, 1992). Klapper, Laeven, and Rajan (2012) further shows that trade-credit terms vary systematically with buyer and supplier characteristics, indicating that receivable quality depends on both counterparties and contract design. More recent work examines factoring, reverse factoring, platform finance, and buyer-intermediated supplier finance as mechanisms for monetizing receivables within supply chains (Tunca and Zhu, 2018; Kouvelis and Xu, 2021; Huang et al., 2025). The paper speaks to this strand by showing that tokenization—by making receivables cryptographically verifiable and collateralizable—can overcome traditional barriers to receivable financing.

The third strand examines how financial frictions affect firm growth and propagate through production networks. Banerjee and Duflo (2014) document that many SMEs are severely credit constrained and have strikingly high marginal returns to capital. Trade credit can support growth where formal financial institutions are weak (Fisman and Love, 2003), but its supply also depends on bank credit conditions and can contract during finan-

cial crises (Love, Preve, and Sarria-Allende, 2007). Access to external finance affects firm growth more generally (Brown and Earle, 2017), and new financial intermediaries, including FinTech and nonbank lenders, can expand credit to small businesses and entrepreneurs (Gopal and Schnabl, 2022; Hau et al., 2024). Recent work emphasizes that working-capital finance operates through receivables and inventories (Almeida, Carvalho, and Kim, 2024), and that trade credit is shaped by firms' positions in production networks and can stabilize supply-chain relationships (Gofman and Wu, 2022; Ersahin, Giannetti, and Huang, 2024). The paper's finding that TAR adoption relaxes upstream credit constraints and generates asymmetric gains across supply chain tiers directly engages with this work. The comparative statics on liquidity constraints and supply chain complexity also align with recent research on production networks and financial multipliers.

2 A Model of Tokenized Accounts Receivable

This section develops a stylized three-echelon model of a supply chain in which tokenized accounts receivable (TAR) relax collateral constraints faced by upstream suppliers. We characterize the equilibrium production decision of the midstream firm both with and without TAR, decompose the welfare gain into a *direct* collateral channel and an *indirect* production-expansion channel, and derive comparative statics with respect to upstream liquidity and supply-chain complexity. The analysis motivates the five empirical hypotheses.

2.1 Environment

Agents and technology. Time is discrete and the economy consists of a single period. The supply chain comprises three echelons, indexed by $\ell \in \{D, M, U\}$:

(i) A *downstream* firm ($\ell = D$), a state-owned enterprise (SOE) that issues final demand;

(ii) A *midstream* firm ($\ell = M$) that transforms raw materials into intermediate goods sold exclusively to the SOE; and

(iii) A finite set of $N \in \mathbb{N}_{++}$ *upstream* firms ($\ell = U$), each supplying a measure $1/N$ of raw materials to the midstream firm.

Let $m \in \mathbb{R}_+$ denote the midstream firm's output, with associated production cost $C(m)$. Each delivered unit yields revenue $r > 0$; non-delivery results in a loss of the unit's variable input cost, normalized to one. The probability that the midstream firm successfully delivers the full quantity m to the SOE is denoted $P(m) \in [0, 1]$.

Assumption 2.1 (Cost function)**.** The cost function $C : \mathbb{R}_+ \to \mathbb{R}_+$ is twice continuously differentiable, strictly increasing, and strictly convex:

$$C \in C^2(\mathbb{R}_+), \qquad C'(m) > 0, \qquad C''(m) > 0 \quad \forall\, m \geq 0,$$

with $C(0) = 0$ and the Inada-style condition $C'(0) < r$ guaranteeing an interior solution.

Assumption 2.2 (Delivery technology)**.** The delivery probability $P : \mathbb{R}_+ \to (0, 1]$ satisfies $P \in C^2(\mathbb{R}_+)$, $P(0) = 1$, $P'(m) \leq 0$, and $P''(m) \leq 0$, with strict inequalities on $(0, \infty)$ in the regime without TAR.

Under Assumption 2.2, the introduction of TAR is captured by the boundary case $P(m) \equiv 1$: tokenization permits upstream suppliers to pledge the SOE's payment obligations as collateral, thereby eliminating the liquidity-driven delivery risk that would otherwise depress $P(m)$ below unity.

Information and timing. The SOE's demand schedule, the cost function $C(\cdot)$, and the delivery technology $P(\cdot)$ are common knowledge. The midstream firm chooses m to maximize expected profit, taking the regime—with or without TAR—as exogenously given. We denote by $\Pi_\tau(m)$ the expected profit under regime $\tau \in \{0, 1\}$, where $\tau = 1$ indicates the presence of TAR.

2.2 The Midstream Firm's Problem

The midstream firm's expected profit, in either regime, is given by

$$\Pi_\tau(m) \;=\; \underbrace{m\,r\,P_\tau(m)}_{\text{expected revenue}} \;-\; \underbrace{m\Big(1-P_\tau(m)\Big)}_{\text{expected loss}} \;-\; \underbrace{C(m)}_{\text{production cost}} \;=\; m\Big(1+r\Big)P_\tau(m) - m - C(m), \tag{1}$$

where $P_1(m) \equiv 1$ and $P_0(m) = P(m)$ satisfies Assumption 2.2.

Proposition 2.1 (Existence and uniqueness of the optimum)**.** *Under Assumptions 2.1–2.2, the program* $\max_{m\geq 0} \Pi_\tau(m)$ *admits a unique interior solution* $m_\tau^\star$ *for each* $\tau \in \{0,1\}$*, characterized by the first-order condition*

$$\Big(1+r\Big)\Big[P_\tau(m_\tau^\star) + m_\tau^\star P_\tau'(m_\tau^\star)\Big] \;=\; 1 + C'(m_\tau^\star). \tag{2}$$

In particular,

$$\textit{With TAR } (\tau=1): \quad C'(m_1^\star) \;=\; r, \tag{3}$$

$$\textit{No TAR } (\tau=0): \quad (1+r)\Big[P(m_0^\star) + m_0^\star P'(m_0^\star)\Big] \;=\; 1 + C'(m_0^\star). \tag{4}$$

Proof. Differentiating (1) twice yields

$$\Pi_\tau''(m) \;=\; 2(1+r)P_\tau'(m) + m(1+r)P_\tau''(m) - C''(m).$$

For $\tau = 1$, $P_1' \equiv P_1'' \equiv 0$, so $\Pi_1''(m) = -C''(m) < 0$. For $\tau = 0$, Assumption 2.2 ensures $P'(m) \leq 0$ and $P''(m) \leq 0$, while Assumption 2.1 ensures $C''(m) > 0$; hence $\Pi_0''(m) < 0$. Strict concavity in both cases delivers uniqueness. Existence of an interior optimum follows from $\Pi_\tau'(0) = r - C'(0) > 0$ and $\lim_{m\to\infty} \Pi_\tau'(m) = -\infty$, the latter implied by strict convexity of $C(\cdot)$. □

Corollary 2.1 (Production expansion)**.** *Let $m_0^\star$ and $m_1^\star$ denote, respectively, the optimal output without and with TAR. Then*

$$m_1^\star \;>\; m_0^\star.$$

Proof. Equation (4) requires $C'(m_0^\star) < r$, since $P(m_0^\star) + m_0^\star P'(m_0^\star) < P(m_0^\star) \leq 1$. Equation (3) gives $C'(m_1^\star) = r$. Strict monotonicity of $C'(\cdot)$ then implies $m_1^\star > m_0^\star$. □

Corollary 2.1 formalizes the *indirect effect* of TAR: even though the midstream firm does not itself hold tokens, anticipated liquidity relief among its upstream suppliers raises its optimal scale of production. Combined with the *direct effect*—collateralizable tokens in the hands of upstream firms—this yields our first testable prediction.

Hypothesis 1 (Universal gains from TAR). The introduction of tokenized accounts receivable raises expected profits and output across all firms in the supply chain.

2.3 A Microfoundation for the Delivery Technology

We now derive $P(m)$ from primitives at the upstream tier. Each of the N upstream suppliers must finance a working-capital position proportional to its share of midstream output, namely m/N. Because the midstream firm's receivables cannot be pledged as collateral in the no-TAR regime, each supplier's individual delivery probability is a function $F : \mathbb{R}_+ \to (0, 1]$ of its working-capital exposure m/N.

Assumption 2.3 (Upstream delivery technology)**.** The function $F : \mathbb{R}_+ \to (0, 1]$ is twice continuously differentiable, with $F(0) = 1$, $F'(x) < 0$, and $F''(x) < 0$ for $x > 0$.

Conditional on independent supplier-level shocks, the aggregate delivery probability is

$$P(m) \;=\; \left[F\left(\tfrac{m}{N}\right)\right]^N. \tag{5}$$

Differentiating (5) and writing $x \equiv m/N$,

$$P'(m) \;=\; F'(x)\Big[F(x)\Big]^{N-1} \;<\; 0,$$

since $F'(x) < 0$ and $F(x) > 0$. A second differentiation yields

$$P''(m) \;=\; \frac{N-1}{N}\Big[F(x)\Big]^{N-2}\Big[F'(x)\Big]^2 \;+\; \frac{1}{N}\Big[F(x)\Big]^{N-1}F''(x).$$

The first term is non-negative, so $P''(m) < 0$ requires $F''(x) < 0$ with magnitude sufficient to dominate. Assumption 2.3 is therefore consistent with Assumption 2.2.

The direct effect—collateral value newly available to upstream suppliers—is largest for firms most liquidity-constrained, and therefore declines with downstream position. The indirect effect—production expansion at the midstream—is, by construction, concentrated nearer the core of the chain. The relative magnitudes of the two channels depend on the curvature of $F(\cdot)$ and on r, and cannot be signed without further restrictions. We therefore advance two competing empirical hypotheses.

Hypothesis 2A (Direct effect dominates). Upstream firms benefit more from the introduction of tokenized accounts receivable than firms closer to the core enterprise.

Hypothesis 2B (Indirect effect dominates). Firms closer to the core enterprise benefit more from the introduction of tokenized accounts receivable than upstream firms.

2.4 Comparative Statics

We now characterize how the indirect benefit $\Delta m^\star \equiv m_1^\star - m_0^\star$ varies with (i) upstream liquidity, indexed by a parameter λ that shifts the supplier-level survival function F, and (ii) supply-chain complexity, indexed by the number of upstream suppliers N.

Substituting the microfoundation (5) into the no-TAR first-order condition (4) yields

$$\underbrace{\big(1+r\big)\Big[F(m/N)\Big]^{N}\left[1 \;+\; \frac{m}{N}\cdot\frac{F'(m/N)}{F(m/N)}\right] \;-\; 1 \;-\; C'(m)}_{\equiv\; \Phi(m;\,\lambda,N)} \;=\; 0,$$

which implicitly defines the no-TAR optimum $m_0^\star$ as a function of λ and N. By strict concavity of $\Pi_0(\cdot)$, $\partial\Phi/\partial m < 0$ at $m_0^\star$; hence the implicit function theorem gives

$$\frac{\partial m_0^\star}{\partial\theta} \;=\; -\,\frac{\partial\Phi/\partial\theta}{\partial\Phi/\partial m} \;\text{ has the same sign as }\; \frac{\partial\Phi}{\partial\theta}, \qquad \theta\in\{\lambda,N\}.$$

Since $m_1^\star$ is pinned down by $C'(m_1^\star)=r$ and is therefore independent of both λ and N, the sign of $\partial\Delta m^\star/\partial\theta$ is the *opposite* of the sign of $\partial\Phi/\partial\theta$.

Proposition 2.2 (Upstream liquidity)**.** *Suppose that a tightening of upstream liquidity—an increase in λ—lowers $F(x)$ and raises $|F'(x)|$ pointwise for all $x>0$. Then*

$$\frac{\partial m_0^\star}{\partial\lambda} \;<\; 0, \qquad \frac{\partial\Delta m^\star}{\partial\lambda} \;>\; 0.$$

Proof. Under the stated monotone shift, both $[F(m/N)]^N$ and the bracketed correction term $1+(m/N)\,F'(m/N)/F(m/N)$ decline at any fixed m, since F falls and F'/F becomes more negative. Hence $\partial\Phi/\partial\lambda<0$ at $m_0^\star$, and by the implicit function theorem $\partial m_0^\star/\partial\lambda<0$. Because $m_1^\star$ does not depend on λ, the gap $\Delta m^\star = m_1^\star - m_0^\star$ widens. □

Proposition 2.3 (Supply-chain complexity)**.** *Treating N as a continuous parameter,*

$$\frac{\partial m_0^\star}{\partial N} \;>\; 0, \qquad \frac{\partial\Delta m^\star}{\partial N} \;<\; 0.$$

Proof. Two channels raise Φ when N increases. First,

$$\Big[F(m/N)\Big]^{N} \;=\; \exp\Big[\,N\log F(m/N)\Big]$$

is monotonically increasing in N for any fixed $m > 0$; this follows from the elementary inequality that $(1 - c/x)^x$ is increasing in x for $x > c > 0$, applied to a first-order expansion of $\log F$. Second, the bracketed correction term

$$1 + \frac{m}{N} \cdot \frac{F'(m/N)}{F(m/N)}$$

is also increasing in N, because as N rises the argument m/N falls, driving $F(m/N) \to 1$ and $|F'(m/N)|$ toward zero by Assumption 2.3. Hence $\partial\Phi/\partial N > 0$ at $m_0^\star$, and by the implicit function theorem $\partial m_0^\star/\partial N > 0$. Since $m_1^\star$ is independent of N, the gap $\Delta m^\star$ narrows. □

The economic intuition is straightforward: a broader upstream base spreads the working-capital burden across a larger number of suppliers, so each supplier's individual exposure m/N shrinks and the friction that TAR relaxes is correspondingly milder. We summarize:

Hypothesis 3A (Liquidity amplification). The marginal benefit of tokenized accounts receivable is increasing in the tightness of upstream liquidity constraints:

$$\frac{\partial\left(m_1^\star - m_0^\star\right)}{\partial\lambda} > 0,$$

where λ indexes the severity of upstream financing frictions. Empirically, this implies a larger TAR elasticity for firms whose customers are more liquidity-constrained.

Hypothesis 3B (Complexity attenuation). The marginal benefit of tokenized accounts receivable is decreasing in the breadth of the upstream-supplier base:

$$\frac{\partial\left(m_1^\star - m_0^\star\right)}{\partial N} < 0.$$

Empirically, this implies a smaller TAR elasticity for firms with a larger number of suppliers, as a wider supplier base diffuses the working-capital burden that TAR is designed to relieve.

3 Background and Data

This section provides the institutional context and data underlying our empirical analysis. We first trace the evolution of supply-chain finance in China, from the structural credit mismatch between state-owned enterprises (SOEs) and their small and medium-sized suppliers to the emergence of tokenized accounts receivable (TAR). We then describe our two principal datasets and construct our central measure of firm-level TAR exposure, before documenting descriptive patterns of firm growth that motivate the subsequent analysis.

3.1 Historical Background

3.1.1 SOEs, SME Suppliers, and the Credit Mismatch

State-owned enterprises (SOEs) have long occupied a central position in China's economic development. Between 1998 and 2024, SOEs consistently accounted for more than 8% of total industrial income and held over 37% of total industrial assets (Appendix Figure IA1). At the same time, market-oriented reforms have spurred rapid private-sector growth: the SOE share of industrial assets fell from 68.84% in 1998 to 37.84% in 2024. Despite this secular decline, SOEs continue to dominate the execution of large-scale infrastructure projects—such as the construction of high-speed rail networks and rolling stock—and roughly 96% of their upstream suppliers are small and medium-sized private enterprises (SMEs).

A fundamental credit mismatch pervades these SOE–SME supply chains. Downstream SOEs enjoy abundant, even surplus, high-quality credit that remains effectively inaccessible to their upstream suppliers. SMEs, in turn, struggle to convert the payment obligations owed to them by SOEs into working capital, because financial institutions have limited incentives to serve them: the profit margins on individual SME transactions are thin, whereas due-diligence and risk-management costs are high.[1] As a result, SMEs face elevated financing

[1] Adhering to principles of prudent operation, financial institutions tend to prioritize the borrowing enterprise's own qualifications, financial condition, and collateral over the core enterprise's credit endorsement when assessing risk. Moreover, while the profit margins on transactions with micro, small, and medium-sized enterprises are thin, the costs of due diligence and risk management remain comparatively high.

costs, constrained access to capital, and heightened bankruptcy risk.

3.1.2 Traditional Supply-Chain Finance

Traditional supply-chain finance (SCF) instruments—principally factoring and commercial bills—emerged in the early years as the primary market response to this credit mismatch. Banks and factoring companies provided financing to suppliers against accounts receivable or payment commitments confirmed by downstream SOEs. China now hosts the world's largest factoring market, accounting for 26% of global volume in 2024, followed by Spain (18%), Italy (11%), and France (8%) (Factors Chain International, 2024 Annual Review). In parallel, core enterprises—including SOEs—have employed commercial bills, particularly bank-accepted bills, as instruments for deferred payment and financing. The Chinese government has further promoted the securitization of supply-chain commercial bills with the aim of channeling bond-market funds toward private SMEs.[2]

3.1.3 The Introduction of Tokenized Accounts Receivable (TAR)

Traditional SCF arrangements, however, fail to address counterparty risk for deeper-tier SMEs because of limited supply-chain visibility. Financing facilities that downstream SOEs extend to their direct (tier-1) suppliers do not effectively pass through to higher tiers of the supply chain. Two frictions impede this pass-through. First, a tier-1 supplier of an SOE lacks the credibility to assure its own suppliers that the accounts receivable it holds—owed by the SOE—are low-risk. Second, even if the underlying contractual relationship with the SOE is verifiable, there is no guarantee that the tier-1 supplier will remit payment to its own suppliers promptly upon receiving funds from the SOE, rather than diverting those funds to alternative uses.

To address these visibility and credibility frictions, a blockchain-based innovation—tokenized accounts receivable (TAR)—was introduced. As established in prior work, blockchain

[2]In August 2019, the Shanghai Commercial Paper Exchange issued the first product portfolio combining supply-chain bills and standardized bills.

technology can enhance supply-chain transparency and enable core enterprises to design effective deep-tier financing mechanisms (Dong, Qiu, and Xu, 2023). TARs represent a paradigmatic application of this technology and differ from traditional SCF instruments along two key dimensions. First, every firm in the supply chain can cryptographically verify the identity of the TAR issuer (i.e., the downstream SOE), which mitigates information asymmetry and translates into a lower discount rate when factoring. Second, firms can directly pay their own suppliers with the TAR they hold, without incurring additional transaction costs.

Two further observations are in order. First, every firm in the supply chain has a strict incentive to accept TAR from its immediate downstream counterpart, because TARs are weakly more reliable than the ordinary accounts receivable issued by that counterpart. By extension, TARs issued by SOEs can circulate readily throughout the supply chain. Second, TARs also mitigate the risk of triangular debt arising from circular transactions—a benefit that extends beyond the conceptual framework formalized in Section 2. With TAR in place, firms can settle mutual obligations using TAR rather than their own accounts receivable, thereby reducing netting frictions.

How Blockchain Technology Enables TAR

Blockchain technology originated with public, permissionless ledgers (e.g., Bitcoin), which enable distributed consensus without recourse to a central authority. The emergence of smart-contract platforms (e.g., Ethereum) in 2015 further rendered digital assets and business logic programmable. Subsequent generations of permissioned blockchains—which restrict access to pre-approved participants—introduced enhanced governance mechanisms, identity-verification tools, and privacy controls. Most recently, tokenization infrastructure—encompassing technical standards, asset-custody solutions, regulatory-compliance frameworks, cross-chain interoperability protocols, and privacy-preserving technologies—has gained widespread adoption. Its core objective is to represent real-world assets and rights on-chain while ensuring seamless integration with existing legal, accounting, and payment systems.

Technically, TAR are issued on permissioned blockchains using this tokenization infrastructure.

From an economic standpoint, blockchain enables TAR through two complementary channels. First, the decentralized architecture provides authorized parties (e.g., buyers, suppliers, banks or factors, and auditors) with a shared, tamper-evident record of each receivable's full lifecycle—from issuance and buyer confirmation, through transfer, pledging, partial splitting, and release, to final settlement. This immutable audit trail reduces reconciliation costs and enhances the traceability of ownership and lien status—capabilities that are critical for mitigating duplicate-financing risk. Second, smart contracts can automate compliance with eligibility rules (such as pre-approved buyer lists, concentration limits, maturity terms, and dispute flags) and streamline financing workflows, thereby lowering the fixed costs that would otherwise render small-ticket receivables financing uneconomical.

3.1.4 The Development of Tokenized Accounts Receivable

In 2015, Cloudchain Group was established with investment from several major SOEs, including CSR Corporation and CNR Corporation, which subsequently merged to form CRRC Corporation.[3] The founding SOEs envisioned Cloudchain Group as a solution to the pressing financing needs of SMEs in their supply chains. For this reason, the downstream enterprises served by the platform are predominantly SOEs. Shortly after its launch, Cloudchain Group rolled out *Cloud-Certificate*, which, to the best of our knowledge, is the first TAR product worldwide. The inaugural TAR was issued in September 2015 by CRRC, the platform's primary founding SOE.

As stated in its Hong Kong Stock Exchange prospectus, Cloudchain Group's cumulative volume of confirmed accounts receivable exceeded RMB 2 trillion as of January 2025. By the end of 2024, its user base spanned 98% of China's prefecture-level regions and encompassed 6,601 core enterprises that issue TAR, 546,413 supply-chain affiliate enterprises, and 3,574

[3]The full name of CRRC is China Railway Rolling Stock Corporation.

affiliated financial institutions.

According to Frost & Sullivan, the market size of China's accounts-receivable e-confirmation platforms reached RMB 4.4 trillion in 2024, equivalent to roughly 3.6% of China's GDP. Cloudchain Group leads this segment with the largest market share, at approximately 15%. The market registered a compound annual growth rate of 35.2% between 2020 and 2024, and Frost & Sullivan projects continued expansion at a compound annual growth rate of 23.2% over 2025–2029.

3.2 Data Description

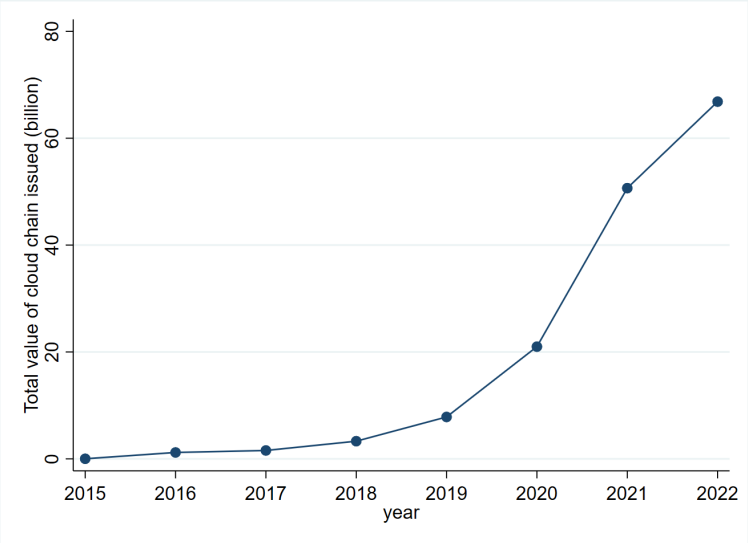
Our empirical analysis draws on two unique datasets pertaining to China. We describe each in turn.

Data from Cloudchain Group. We obtain administrative Cloud-Certificate data from Cloudchain Group Co., Ltd., the first enterprise to provide TAR services. In accordance with Cloudchain Group's privacy-compliance protocols, the dataset is confidential and was processed offline throughout this study.

The dataset comprises transaction and factoring records spanning January 2020 to January 2021, with 23,824 transaction records and 9,954 factoring records. It covers 13,309 firms, including 589 core enterprises that have issued TAR; cumulative transaction volume amounts to RMB 29.03 billion. Each record contains a unique TAR identifier, generated at issuance by the originating SOE and preserved across all subsequent transfers. The record also specifies the TAR tier—namely, the number of transfers preceding the current holder—together with granular information on the TAR's issuer, current holder, and transferor.

We supplement this core dataset with annual aggregate issuance data for the ten largest core issuers (ranked by issuance volume) from 2015 to 2023, together with interim data covering January–August 2024. Figure 1 documents a sharp rise in aggregate TAR issuance over the sample period—from RMB 20 million in 2015 to RMB 66.84 billion in 2022. These ten core issuers are concentrated in the construction and infrastructure industries. Our

Figure 1. TAR Issuance by Top Ten Core Enterprises



Notes: This figure plots the aggregate issuance volume of the ten core cloud-chain issuers over time.

empirical analysis focuses exclusively on the 7,496 firms that received TAR from the group companies of these ten core issuers, yielding a final sample of 14,786 transaction records with an aggregate volume of RMB 14.80 billion.[4]

Annual Government Survey. We obtain firm-level financial data from the State Administration for Industry and Commerce of China for the period 2014–2022. The dataset comprises comprehensive financial statements of all non-military enterprises in China and reports total assets, total liabilities, shareholders' equity, main business income, net income, and taxes paid. From these primary variables, we compute the effective tax rate as taxes paid divided by main business income and the return on equity (ROE) as net income divided by shareholders' equity. We verify that the survey covers all 13,178 private and 131 listed firms that receive TAR in the Cloudchain dataset, enabling us to merge the two datasets by firm name.

Although the survey data are self-reported by enterprises, the data-sharing arrange-

[4]The group companies are the large Chinese central state-owned enterprise (SOE) conglomerate that serves as the parent of one or more core firms.

ments within China's central government ensure their reliability. The State Administration for Industry and Commerce cross-checks self-reported figures against official tax records, and the state taxation authority obtains comprehensive enterprise operating data through routine tax-collection procedures. Crucially, the annual reporting window (June) falls after the completion of tax settlements (May). Because operating data are already finalized at the time of reporting, enterprises have little incentive to submit inaccurate information.

3.3 TAR Exposure

The unit of observation in our raw data is the value of TAR issued by a core firm and held by one of its suppliers. Each core firm belongs to a Group (a central SOE conglomerate), which may parent multiple issuing firms. Because supplier-level holding records are observed in only a single year, while our empirical analysis requires a supplier-year measure of TAR exposure over 2014–2022, we use the cross-sectional holder distribution observed in that year to impute exposure for the remaining years.

Specifically, we assume that, within each Group, the share of TAR held by a given supplier relative to the Group's total TAR issuance is time-invariant over the sample period. We compute this share using 2020, the only year for which supplier-level holdings are observed in our data:

$$\hat{s}_{h,g} \;=\; \frac{\text{Held}_{h,g,2020}}{\text{Issued}_{g,2020}}, \tag{6}$$

where $\text{Held}_{h,g,2020}$ is the RMB value of TAR issued by core firms in Group g and held by supplier h in 2020, and $\text{Issued}_{g,2020}$ is the total RMB value of TAR issued by all core firms in Group g in 2020. By construction, $\sum_h s_{h,g} \leq 1$, with the residual reflecting TAR held by parties outside our observed supplier sample (e.g., financial intermediaries or unobserved suppliers).

The TAR held by supplier h from Group g in year t is then imputed as

$$\text{Held}_{h,g,t} \;=\; s_{h,g} \cdot \text{Issued}_{g,t}, \qquad t = 2014, \ldots, 2022,$$

where $\text{Issued}_{g,t}$ is observed directly from Group-level issuance records. Supplier h's total TAR exposure in year t is obtained by aggregating across all Groups from which the supplier receives TAR:

$$\text{Exposure}_{h,t} \;=\; \sum_{g} \text{Held}_{h,g,t} \;=\; \sum_{g} s_{h,g} \cdot \text{Issued}_{g,t}.$$

The variable $\text{Exposure}_{h,t}$, measured in RMB, serves as our central supplier–year measure of TAR participation throughout the empirical analysis.

A numerical illustration. To fix ideas, consider a stylized example with two Groups, $g \in \{A, B\}$, and two suppliers, $h \in \{1, 2\}$. Suppose that in the observation year (2020), the Group-level TAR issuance and supplier-level holdings (in RMB millions) are:

	Group A	Group B	Supplier total
Supplier 1 holds	30	10	40
Supplier 2 holds	20	0	20
Group total issuance	100	50	—

Note that holdings sum to less than issuance within each Group ($30 + 20 < 100$ for A; $10 + 0 < 50$ for B), reflecting TAR held by parties outside the observed supplier sample (e.g., banks or factoring companies to which suppliers have discounted their TAR).

Applying Equation (6), the estimated holder shares are

$$\hat{s}_{1,A} = \tfrac{30}{100} = 0.30, \quad \hat{s}_{2,A} = \tfrac{20}{100} = 0.20, \quad \hat{s}_{1,B} = \tfrac{10}{50} = 0.20, \quad \hat{s}_{2,B} = 0.$$

These shares are assumed to be constant over 2014–2022. Suppose that Group-level issuance, which is observed directly in every year, evolves as

$$\text{Issued}_{A,2019} = 80, \;\; \text{Issued}_{A,2021} = 120; \qquad \text{Issued}_{B,2019} = 40, \;\; \text{Issued}_{B,2021} = 60.$$

Imputed holdings and total exposure for Supplier 1 in 2019 and 2021 are then

$$\text{Exposure}_{1,2019} = \hat{s}_{1,A} \cdot 80 + \hat{s}_{1,B} \cdot 40 = 0.30(80) + 0.20(40) = 32,$$
$$\text{Exposure}_{1,2021} = \hat{s}_{1,A} \cdot 120 + \hat{s}_{1,B} \cdot 60 = 0.30(120) + 0.20(60) = 48.$$

The construction thus translates time variation in Group-level issuance—which is observed throughout the sample—into supplier-level variation in TAR exposure, weighted by each supplier's 2020 holder share within each Group.

3.4 Descriptive Patterns of Firm Growth

We partition firms into treatment and control groups based on their percentile in the cross-sectional distribution of $\text{Exposure}_{h,2020}$. Firms in the top decile (between the 90th and 100th percentiles) are designated as treated, capturing those most deeply involved in the cloud-chain platform. Firms at or below the median (50th percentile) form the control group, representing firms with little or no platform participation. To assess the validity of the research design, we additionally define a placebo treatment group consisting of firms between the 40th and 50th percentiles of the TAR-exposure distribution, with firms below the 40th percentile serving as the corresponding placebo control group.

To minimize systematic differences in observable characteristics between treated and control firms, we match firms using propensity scores estimated from *pre-treatment* (2014) financial data. The matching covariates are total assets, main business income, total liabilities, and the number of employees. Matching is conducted on a one-to-one nearest-neighbor basis without replacement: for each treated firm, we select the control firm with the closest propensity score as its match, and each control firm is used at most once, thereby preserving the independence of matched pairs.

We then construct a balanced firm-year panel covering 2015–2022 by inserting missing firm-year records. Missing values for total assets, operating revenue, and total liabilities are imputed via linear interpolation, with endpoint gaps filled by forward or backward

extrapolation. To prevent large firms from disproportionately influencing the estimated treatment effects, we further exclude treated firms above the 95th percentile of total assets, operating revenue, or total liabilities in 2014. Finally, to enhance homogeneity in the timing of treatment, we restrict attention to firms that first adopted TAR in 2016. These restrictions, combined with one-to-one matching, yield 75 matched pairs in the real treatment group and 41 matched pairs in the placebo group.

Figure 2. Effects of TAR on Firm Growth

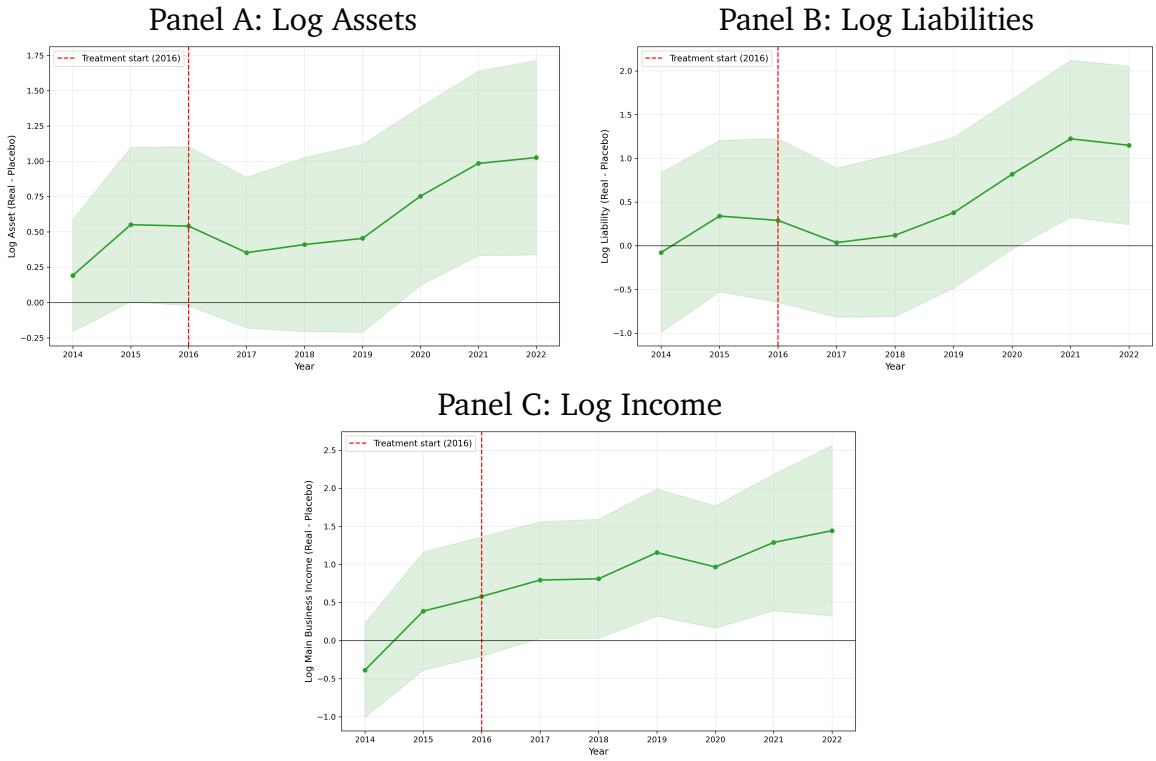


Notes: The figure plots the estimated effects for the real and placebo treatment groups over time. Shaded areas denote 95% confidence intervals.

Figure 2 plots the year-by-year differences in log financial outcomes between treated firms and their propensity-score-matched controls, alongside the analogous placebo comparison. For total assets, total liabilities, and main business income, the real treatment series exhibits a clear post-2016 increase relative to matched controls, while pre-treatment differences are comparatively modest. By contrast, the placebo series remains close to zero

throughout and displays weaker, less persistent post-treatment divergence. Taken together, these patterns suggest that firms deeply involved in the TAR platform experienced markedly stronger subsequent growth in scale and financial activity, and that the estimated effects are unlikely to reflect common trends or artifacts of the matching procedure alone.

Figure 3. Real Minus Placebo Effects of TAR on Firm Growth



Notes: The figure plots the difference between the estimated effects for the real and placebo treatment groups over time. Shaded areas denote 95% confidence intervals.

Figure 3 plots the year-by-year difference between the real and placebo treatment effects on log financial outcomes, together with the associated 95% confidence bands. Although the treatment is dated to 2016, the economic effects need not materialize immediately, as firms' exposure to the platform expanded gradually over time. Consistent with this lagged adjustment, the real–placebo gap begins to widen after 2018 and becomes statistically significantly positive after 2020 for both total assets and total liabilities. For main business income, the gap widens earlier and becomes statistically significantly positive after 2017.

This timing is consistent with the sharp increase in the issuance size of cloud chain for the core Group after 2020, as shown in Figure 1. Overall, these patterns suggest that firms more deeply involved in the platform experienced stronger subsequent growth in scale and financial activity.

4 Empirical Strategy

This section describes the construction of our key variables and the empirical design used to evaluate the real effects of tokenized accounts receivable (TAR) adoption. We first outline our identification strategy, which exploits the staggered adoption of TAR by state-owned enterprises (SOEs) as a plausibly exogenous shock to upstream small and medium-sized enterprises (SMEs). We then describe how we construct the key firm-level variables—TAR tier, liquidity constraint, and supplier size—and present the regression specifications.

4.1 Identification Strategy

SOEs' adoption of TAR provides a plausibly exogenous shock to SMEs in their supply chains, because such adoption decisions are unlikely to be correlated with unobservable SME characteristics. The shareholder structure of the Cloudchain Group appears to be a key driver of SOE adoption: the very first TAR issuance was launched by a founding shareholder of the Cloudchain Group, and the only issuer among the top ten core SOEs in 2015 was likewise a founding shareholder.

We offer three additional remarks supporting this exogeneity assumption. First, SOEs in China are primarily accountable to the central government, and their decisions tend to align with central-government priorities—such as ensuring the security of TAR and advancing policy initiatives that endorse its adoption (e.g., promoting inclusive finance or leveraging the digital economy to empower the real economy). Consequently, SOEs typically scale up TAR deployment gradually during the initial adoption phase to mitigate risk, or adopt a wait-and-see approach until peer SOEs have demonstrated the technology in practice. Second, it is impractical for an SOE to tailor its TAR adoption decision to any specific upstream

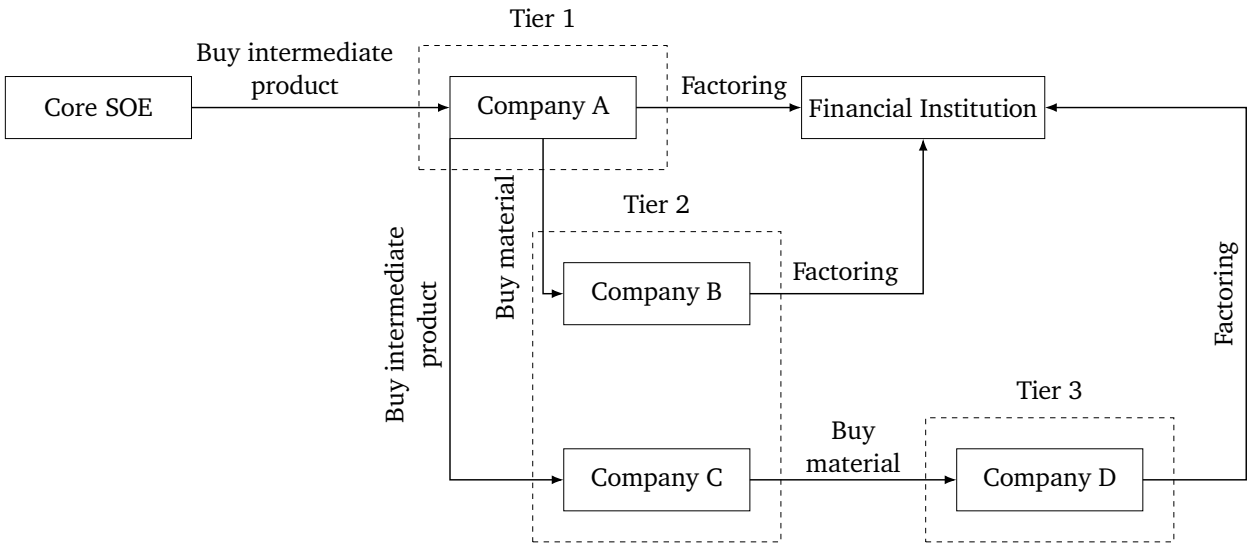
firm, since each SOE typically has tens of thousands of enterprises in its supply network. For example, China Mobile (CMCC) has roughly 17,000 supply-chain partners, while CRRC's supplier base exceeds 86,000 firms. Third, once an SOE adopts TAR, upstream SMEs are unlikely to decline participation, because (i) the associated switching costs are negligible,[5] (ii) participation yields tangible benefits for SMEs, and (iii) SMEs lack the bargaining power to override the SOE's decision.

4.2 Variable Constructions

We construct explanatory variables that are used in testing Hypotheses 2, 3A, and 3B.

TAR Tier. Testing Hypothesis 2 requires a unique characterization of each holder's position within the supply chain. Figure 4 illustrates a canonical flow of TAR across firms in a supply chain.

Figure 4. Flow of Tokenized Accounts Receivable



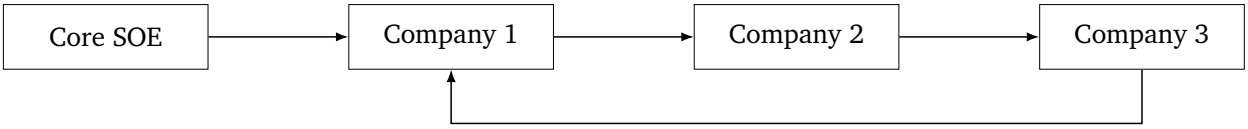
The sequence begins with a core SOE issuing TAR to procure intermediate goods from Company A. Company A then has two options: (i) discount the TAR with a financial institution to obtain immediate liquidity, or (ii) use the TAR to purchase raw materials from

[5] Owing to the nature of blockchain, all TAR operations can be conducted fully online, eliminating the costs of in-person factoring visits and physical document preparation.

Company B or intermediate goods from Company C. Company B, in turn, may either hold the TAR until maturity to receive full payment directly from the core SOE, or discount it to secure working capital for production. Company C, meanwhile, may deploy the TAR to settle its own procurement from Company D, which at the final stage of the chain faces the same binary choice as Company B. Based on their position in the supply chain, we classify Company A as a tier-1 supplier, Companies B and C as tier-2 suppliers, and Company D as a tier-3 supplier.

A single firm may be assigned multiple tiers within one TAR issuance due to circular supply-chain transactions. Figure 5 illustrates such a loop: Company 1 receives a TAR from the core SOE and passes it to Company 2, which uses it to pay Company 3 for raw materials, who in turn pays Company 1 for intermediate goods. Here, Company 1 is classified as both tier-1 and tier-4. To address this, we assign each firm its *minimum* tier within a given issuance, then take the *average* across issuances for firms in multiple TAR programs.

Figure 5. Circular Transaction of TAR



Liquidity Constraint. To test Hypothesis 3A, we construct a measure of firms' liquidity constraints based on the financial conditions of their customers. If Company A transfers a TAR to Company B, we define Company A as a customer of Company B. Specifically, we use the average liability-to-asset ratio across a firm's customers as a proxy for the liquidity pressure it faces. To ensure consistency, we fix each firm's customer base at its 2020 composition throughout the sample period. Formally, the measure is defined as

$$CustLia_{c,t} = \frac{\sum_n Liability_{n,t}}{\sum_n Asset_{n,t}},$$

where $Liability_{n,t}$ and $Asset_{n,t}$ denote, respectively, the total liabilities and total assets of customer n of firm c in year t.

Supplier Size. To test Hypothesis 3B, we construct a measure of each firm's supplier base. Specifically, we use the number of distinct firms that receive TAR from a given firm as a proxy for the size of its supplier network.

Table 1 reports summary statistics for the main variables used in the empirical analysis. The average firm in our sample has a TAR exposure of RMB 1.382 million, with the 95th percentile reaching RMB 5.09 million. The distribution of TAR exposure is highly right-skewed: the 5th and 25th percentiles are both zero, the median is only RMB 0.06 million, and the standard deviation (RMB 8.272 million) is several times larger than the mean. This pronounced cross-sectional dispersion provides ample identifying variation for estimating the relationship between TAR participation and firm-level outcomes.

The table further documents substantial heterogeneity in firm scale and operating activity. To mitigate the influence of extreme outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Mean total assets, total liabilities, and operating income are RMB 193.696, 131.850, and 187.554 million, respectively. These variables display large dispersion, with standard deviations of RMB 675.198, 502.634, and 688.254 million, respectively, and pronounced upper-tail values. Tax payments display a similar pattern, with a mean of RMB 546.625 million and a 95th percentile of RMB 2,734.01 million. Mean ROA, employment measured by the number of employees with social security, and labor productivity[6] are 1.568, 0.867, and 3.069, respectively.

Finally, the supply-chain variables also exhibit considerable variation. The average firm sits at *Tier* 2.06 in the production network, indicating that most sample firms are upstream of, but reasonably close to, the focal downstream buyers. The average customer-side liquidity constraint (*CustLia*) is 0.702, with an interquartile range from 0.569 to 0.854, sug-

[6]Labor productivity is defined as sales per employee.

gesting that the typical firm faces downstream customers that are themselves financially constrained, and that the degree of such constraints varies substantially across firms. The (log) supplier count (*Supplier*) has a mean of 1.09 and a median of 0.693, again pointing to substantial heterogeneity in upstream diversification across firms.

Table 1. Summary Statistics

	Mean	Std	5p	25p	50p	75p	95p
Asset	193.696	675.198	0.474	4.34	17.244	72.831	866.647
Liability	131.85	502.634	0.02	1.924	9.622	42.867	531.12
Income	187.554	688.254	0.013	3.1	15.334	69.48	794.658
Tax paid	546.625	1762.183	0	5.613	39.195	230.099	2734.01
ROA	1.568	10.296	-9.214	0	1.093	3.907	14.601
Employment	2.598	2.002	0	0.693	2.708	3.989	5.999
Labor Prod.	4.869	10.939	0.164	0.607	1.43	3.74	22.612
TAR Exposure	1.382	8.272	0	0	0.06	0.52	5.09
Tier	2.06	1.256	1	1	2	3	4
CustLia	0.702	1.038	0.251	0.569	0.763	0.854	0.974
SupplierCount	1.09	0.739	0.693	0.693	0.693	1.099	2.773

Notes: This table reports summary statistics (mean, standard deviation, and selected percentiles) for the variables used in the empirical analysis. All financial values are expressed in millions of RMB.

4.3 Regression Models

Our analysis is based on a firm-year panel of Chinese firms linked to TAR networks over the period 2014–2022. The panel integrates firm-level financial information with TAR transaction records and core-company issuance data, yielding 33,586 non-missing firm-year observations for 4,719 firms in the main sample. 2,777 companies are dropped because of missing data for assets, liabilities, or main business income. The key explanatory variable is each firm's annual TAR exposure, defined as the natural logarithm of the holder-level exposure value (in RMB millions). Throughout the remainder of the paper, $Exposure_{c,t}$ refers to this logarithmic measure. The outcome variables capture firm scale and performance, including total assets, total liabilities, sales income, tax payments, and profitability.

To test Hypothesis 1, we begin with a within-firm specification that relates firms' finan-

cial outcomes to their TAR exposure:

$$Output_{c,t} = \beta_1 Exposure_{c,t} + \gamma_c + \gamma_t + \alpha + \epsilon_{c,t}, \tag{7}$$

where $Output_{c,t}$ denotes the outcome variable of firm c in year t. We log-transform total assets, liabilities, main business income, taxes paid, and employment using $\log(x) \equiv \ln(x + 1)$, while ROA and labor productivity are used in their raw, untransformed values. $Exposure_{c,t}$ denotes the log of TAR exposure; γ_c and γ_t are firm and year fixed effects, respectively. Standard errors are clustered at the firm level.

Hypotheses 2A and 2B distinguish between two channels through which TAR may affect firms: upstream firms may benefit from lower default risk because TARs are backed by SOEs, whereas downstream firms may benefit from production expansion. Hypotheses 3A and 3B further predict that the effects of TAR are stronger for firms with more liquidity-constrained customers or with fewer suppliers.

To examine these differential and heterogeneous effects within a unified framework, we estimate the following interaction model:

$$Output_{c,t} = \beta_1 Z_{c,t} \times Exposure_{c,t} + \beta_2 Exposure_{c,t} + \gamma_c + \gamma_t + \alpha + \epsilon_{c,t}, \tag{8}$$

where $Output_{c,t}$ denotes the financial characteristics of firm c in year t, $Exposure_{c,t}$ denotes log of TAR exposure, and $Z_{c,t}$ is a moderator that varies across specifications. Specifically, $Z_{c,t}$ is set to: (i) $Tier_c$, the firm's position in the supply chain, to test Hypotheses 2A and 2B; (ii) $CustLia_{c,t}$, customers' liability-to-asset ratio, to test Hypothesis 3A; and (iii) $SupplierCount_c$, the number of suppliers, to test Hypothesis 3B. Note that $Tier_c$ and $Supplier_c$ are firm-specific and time-invariant, whereas $CustLia_{c,t}$ varies over time; the general notation $Z_{c,t}$ subsumes both cases. The coefficient β_1 captures whether the relationship between TAR exposure and firm outcomes varies systematically with the corresponding moderator. Standard errors are clustered at the firm level.

5 Empirical Results

This section presents empirical evidence on how tokenized accounts receivable (TAR) affects firms' growth. Economically, TAR converts receivables backed by the core firm's credit into pledgeable and transferable digital claims. In the model, this relaxes upstream suppliers' financing constraints directly and can also induce the midstream firm to expand production once its suppliers become less constrained. We therefore expect TAR exposure to show up mainly in scale variables (assets, liabilities, sales), tax payments, and profitability. The heterogeneity tests then ask how these gains vary with supply-chain position, customer financial constraints, and the number of suppliers.

5.1 TAR Exposure

Table 2 shows that firms with greater TAR exposure experience larger increases in scale and operating activity. Columns (1)–(3) indicate that a 1% increase in TAR exposure is associated with increases of 0.132% in assets, 0.191% in liabilities, and 0.215% in income, all significant at the 1% level.[7] The fact that the liability elasticity exceeds the asset elasticity indicates that the expansion is debt-financed: the marginal yuan of TAR exposure accrues disproportionately to the right-hand side of the balance sheet, consistent with suppliers using TAR claims as a financing instrument. That the income elasticity exceeds the asset elasticity further points to an improvement in asset turnover—the empirical signature of a relaxed working-capital constraint.

Column (4) reveals a parallel pattern for tax payments: a 1% increase in TAR exposure is associated with a 0.196% increase in taxes paid. This result is consistent with the interpretation that TAR enables firms to expand real activity rather than merely reshuffle financing claims. Column (5) reports a small and statistically insignificant association with ROA. This null is itself informative: because total assets expand substantially in Column (1),

[7]The smaller number of observations in Columns (4) and (5) reflects missing values for taxes paid and net income, respectively. The smaller number of observations in Columns (6) and (7) reflects missing or zero values for employment.

Table 2. Firm Growth and TAR Exposure

	(1) Asset	(2) Liability	(3) Income	(4) Tax	(5) ROA	(6) Employment	(7) Labor Prod.
Exposure	0.132***	0.191***	0.215***	0.196***	0.022	0.007	1.118***
	(0.015)	(0.020)	(0.022)	(0.029)	(0.141)	(0.013)	(0.228)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	33,514	33,514	33,514	33,511	33,508	23,704	17,616

Notes: This table reports the effect of TAR exposure on firm performance. *Exposure* is the log amount of TAR held by the firm. Firm and year fixed effects are included in all regressions. Robust standard errors, clustered at the firm level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

diminishing returns to capital would, absent any offsetting force, predict a decline in ROA. A flat ROA therefore implies that the underlying return on the marginal asset rise enough to neutralize this denominator effect, suggesting a modest improvement in profitability that is masked by balance-sheet growth and rising leverage. Columns (6) and (7) show that a 1% increase in TAR exposure is associated with a 0.007% statistically insignificant increase in the number of employees and a 1.118 percentage-point increase in labor productivity, respectively.

To gauge the effect of fully tokenizing core groups' trade credit, we first estimate the annual flow of newly issued accounts payable implied by reported Days Payable Outstanding (DPO):

$$\text{New Accounts Payable}_t = \frac{\frac{\text{Accounts Payable}_{t-1} + \text{Accounts Payable}_t}{2} \times 365}{\text{Days Payable Outstanding}}$$

In 2022, the eight core Groups[8] in our sample issued RMB 140.20 billion in TARs, equivalent to only 3.19 percent of their estimated annual flow of new accounts payable (RMB 4,401.26 billion). Were these groups to tokenize the entire flow, the implied expansion in supplier-level TAR exposure would be substantial. Applying the elasticities reported in

[8]The core Groups refer to large listed state-owned enterprises (SOEs) in our sample, including China Metallurgical Group Corporation, CRRC Corporation, China Railway Group, China Communications Construction Company, China State Construction Engineering Corporation, Power Construction Corporation of China, China Energy Engineering Corporation, and China Railway Construction Corporation.

Table 2, and assuming they remain constant over this range, suppliers' assets, liabilities, operating income, and tax payments would rise by 57.61, 93.15, 109.81, and 96.51 percent, respectively.

5.2 TAR Tier

While TAR may benefit participating firms on average, its gains need not be evenly distributed across the supply chain. Table 3 examines whether the effect of TAR exposure varies with a firm's TAR tier, where a higher tier corresponds to a position farther from the core enterprise. Columns (1)–(3) show that each additional tier reduces the elasticity of assets, liabilities, and income with respect to TAR exposure by 0.045, 0.077, and 0.004, respectively. The interaction terms are statistically significant for assets and liabilities, but not for income. The insignificant income interaction suggests that the attenuation is more pronounced for financing capacity than for sales activity.

Table 3. Firm Growth and TAR Tier

	(1) Asset	(2) Liability	(3) Income	(4) Tax	(5) ROA	(6) Employment	(7) Labor Prod.
Exposure × *Tier*	-0.045***	-0.077***	-0.004	-0.044**	0.219	-0.008	-0.151
	(0.013)	(0.018)	(0.023)	(0.021)	(0.182)	(0.011)	(0.146)
Exposure	0.194***	0.299***	0.220***	0.257***	-0.282	0.019	1.320***
	(0.024)	(0.032)	(0.037)	(0.046)	(0.253)	(0.021)	(0.333)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	33,514	33,514	33,514	33,511	33,508	23,704	17,616

Notes: This table reports how the effect of TAR exposure varies across supply-chain tiers. *Tier* denotes the firm's TAR tier, and *Exposure* is the log amount of TAR held by the firm. Firm and year fixed effects are included in all regressions. Robust standard errors, clustered at the firm level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Column (4) shows that the tax response attenuates in parallel: each additional tier of distance from the core enterprise reduces the elasticity of taxes paid with respect to TAR exposure by 0.044. Column (5) reports a statistically insignificant interaction for ROA, indicating that profitability neither rises nor falls as TAR circulates deeper into the supply chain.

Read alongside the positive level effects on assets, liabilities, and income in Columns (1)–(3), this flat ROA gradient implies that the return on the marginal assets financed through TAR is broadly stable across tiers, even as the scale of the balance-sheet expansion itself diminishes with distance from the issuing SOE. TAR's benefits thus diffuse less powerfully into deeper tiers, but the investments they finance appear to be of comparable quality wherever in the chain they occur. Columns (6) and (7) further indicates that employment and labor productivity does not vary systematically across tiers.

Taken together, these patterns favor Hypothesis 2B over Hypothesis 2A. Balance-sheet and tax responses are concentrated among firms closer to the core enterprise, while profitability is essentially flat across supply-chain positions. TAR therefore appears to operate less as a simple conduit that transmits collateral value to the most distant suppliers, and more as a mechanism that expands operating capacity in the upper tiers of the supply chain—precisely where its cryptographic guarantees of authenticity and ownership are most directly anchored to the issuing SOE.

5.3 Customer Financial Constraints

We next examine whether TAR exposure has larger real effects when firms transact with financially constrained customers. Table 4 reports that the coefficients on $Exposure \times CustLia$ are positive across all outcome variables. Columns (1)–(3) show that a 10-percentage-point increase in customers' liability-to-asset ratio raises the elasticity of assets, liabilities, and income with respect to TAR exposure by 0.012, 0.024, and 0.014, respectively. The asset and liability estimates are statistically significant at conventional levels, and the income estimate is significant at the 10% level.

The same pattern appears for tax payments and profitability. Column (4) shows that a 10-percentage-point increase in customers' liability-to-asset ratio raises the elasticity of taxes paid with respect to TAR exposure by 0.021. More importantly, Column (5) reports a positive but statistically insignificant interaction for ROA. Columns (6) and (7) further show that a 10-percentage-point increase in customers' liability-to-asset ratio raises the elasticity

Table 4. Firm Growth and Customer Financial Constraints

	(1) Asset	(2) Liability	(3) Income	(4) Tax	(5) ROA	(6) Employment	(7) Labor Prod.
Exposure × *CustLia*	0.119*	0.239***	0.144*	0.205**	0.712	0.188***	1.003
	(0.061)	(0.088)	(0.087)	(0.097)	(0.704)	(0.063)	(0.681)
Exposure	0.004	-0.045	0.085	0.002	-0.552	-0.166***	0.696
	(0.049)	(0.071)	(0.071)	(0.080)	(0.549)	(0.049)	(0.530)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	14,589	14,589	14,589	14,587	14,584	10,296	7,762

Notes: This table reports how the effect of TAR exposure varies with customer financial constraints. *CustLia* is the average liability-to-asset ratio of the firm's customers, and *Exposure* is the log amount of TAR held by the firm. Firm and year fixed effects are included in all regressions. Robust standard errors, clustered at the firm level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

of employment and labor-productivity paid with respect to TAR exposure by 0.019 and 0.100, respectively.

The above results are consistent with the liquidity mechanism in Hypothesis 3A: the more severe the financial friction in the supply chain, the larger the benefit from transforming receivables into TAR because financially weaker customers tend to delay payment or substitute trade credit for bank financing, shifting costs upstream. In this sense, TAR functions less as a uniform subsidy to supply-chain financing and more as a targeted instrument that channels liquidity to precisely the segments where the underlying friction binds hardest.

5.4 Supplier Size

Finally, we examine whether supplier size moderates the effect of TAR exposure. Table 5 reports consistently negative interaction coefficients between TAR exposure and supplier count. Columns (1)–(3) show that a 10% increase in the number of suppliers reduces the elasticity of assets, liabilities, and income with respect to TAR exposure by approximately 0.006, 0.007, and 0.009, respectively. All three interaction coefficients are statistically significant at the 1% level. In this sense, a broad upstream base and TAR are partial substitutes

in providing working capital to the chain: both keep each individual supplier's financing burden manageable, so the marginal value of TAR is largest precisely where suppliers are few and per-supplier exposure is concentrated.

Table 5. Firm Growth and Supplier Size

	(1) Asset	(2) Liability	(3) Income	(4) Tax	(5) ROA	(6) Employment	(7) Labor Prod.
Exposure × *Supplier*	-0.062***	-0.067***	-0.088***	-0.152***	-0.090	-0.021**	-0.119
	(0.013)	(0.015)	(0.019)	(0.044)	(0.151)	(0.010)	(0.279)
Exposure	0.162***	0.178***	0.313***	0.272***	0.330	0.003	1.895**
	(0.039)	(0.050)	(0.063)	(0.080)	(0.488)	(0.037)	(0.829)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	6,576	6,576	6,576	6,575	6,575	5,049	4,142

Notes: This table reports how the effect of TAR exposure varies with supplier size. *SupplierCount* is the log number of the firm's suppliers, and *Exposure* is the log amount of TAR held by the firm. Firm and year fixed effects are included in all regressions. Robust standard errors, clustered at the firm level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Column (4) shows that the tax response also declines with supplier count: a 10% increase in the number of suppliers reduces the elasticity of taxes paid with respect to TAR exposure by approximately 0.015, consistent with the above results. Column (5) reports an interaction coefficient that is essentially zero and statistically insignificant, suggesting no meaningful heterogeneity in ROA. The null result suggests that profitability is shaped by customer-side financial conditions (Table 4) rather than by upstream network breadth. Columns (6) and (7) show that interaction term for employment is negative and statistically significant, indicating that the employment gains associated with TAR exposure are weaker among firms connected to more suppliers. For labor productivity, the interaction term is also negative but statistically insignificant, providing no robust evidence of heterogeneous productivity effects by supplier count. Overall, firms with more concentrated supplier networks capture larger real benefits from TAR, directly confirming Hypothesis 3B.

6 Conclusion

This paper provides the first causal evidence that blockchain technology can generate real economic growth by relaxing financing frictions in supply chains. These gains operate primarily through an indirect production-expansion channel. By alleviating upstream liquidity constraints, TAR enables downstream firms to expand output, concentrating benefits among firms closest to the core enterprise. Consistent with this mechanism, the effects are amplified for firms with more liquidity-constrained customers and attenuated for firms with broader supplier bases, as a wider network already diffuses working-capital burdens.

Our findings carry clear policy implications. Blockchain-based receivables tokenization can serve as a scalable instrument for financial inclusion, particularly in developing economies where credit mismatches between large SOEs and SME suppliers are severe. Regulatory frameworks should support the legal recognition and interoperability of tokenized claims, while recognizing that benefits accrue unevenly—deep-tier suppliers may need complementary interventions. Full tokenization of core SOEs' accounts payable would raise supplier assets, income, and tax payments by 57–110%, underscoring the substantial unrealized potential of this technology. Far from a speculative innovation, TAR represents a genuine financial mechanism that transforms illiquid payment obligations into productive collateral, with measurable effects on firm growth, tax revenues, and supply chain resilience.

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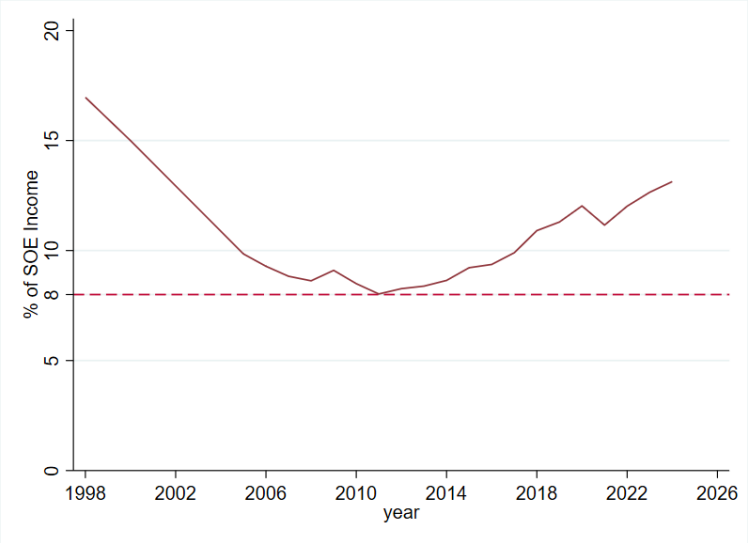
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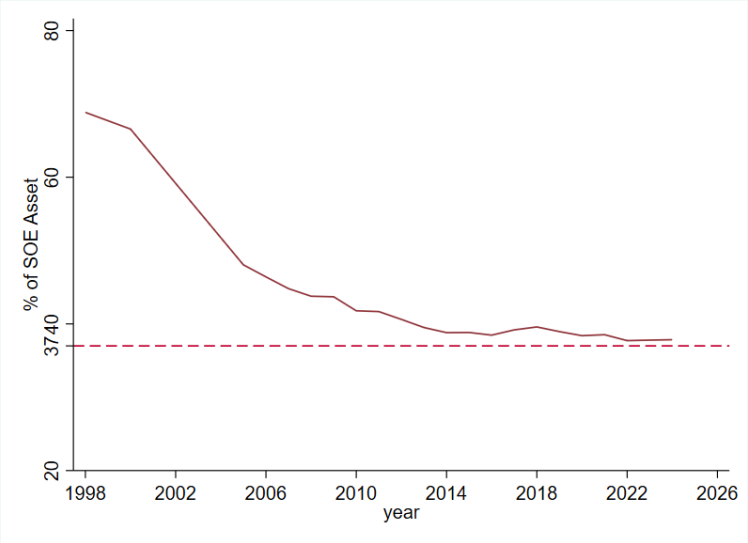
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Figure IA1. Share of SOE Income and Assets in the Industrial Sector

This figure shows the trend of the ratio of SOE income and assets in the industrial sector from 1998 to 2024 in China. Source: State-owned Assets Supervision and Administration Commission. http://www.sasac.gov.cn/n2588020/n2877938/n2879597/n30275940/c31289505/content.html



Panel A: Share of SOE Income



Panel B: Share of SOE Asset