

Does Blockchain Adoption Improve Supply Chain Transparency and Operational Efficiency? Cross-Country Panel Evidence, 2007–2023

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Abstract

Blockchain technology is widely promoted as a means of making supply chains more transparent and efficient, yet quantitative cross-country evidence remains scarce. This study asks whether national-level blockchain adoption is associated with supply chain transparency and operational efficiency. Using a balanced panel of 20 economies observed in seven World Bank Logistics Performance Index (LPI) waves between 2007 and 2023 (140 observations), transparency is proxied by the LPI tracking-and-tracing score and efficiency by the overall LPI score. Blockchain adoption is captured by a composite Blockchain Adoption Index (BAI) constructed from World Development Indicators. Pooled estimates show a positive but statistically insignificant association with both outcomes ($\beta \approx 1.06$ and 1.06). Once country and year fixed effects are included, the within-country effect of the BAI is close to zero for transparency ($\beta = -0.03$, $p = 0.94$) and efficiency ($\beta = -0.06$, $p = 0.89$); hypotheses H1 and H2 are therefore not supported in the baseline specification. The estimates are, however, sensitive to sample composition: excluding Argentina yields a positive and statistically significant efficiency coefficient ($\beta = 0.90$, $p = 0.004$). The results suggest that the strong cross-country correlation between digital capability and logistics performance reflects long-run differences between countries more than measurable within-country gains from rising adoption, and they underline the need for adoption measures that capture actual blockchain deployment.

Keywords: blockchain technology; supply chain transparency; operational efficiency; Logistics Performance Index; panel data; fixed effects

1. Introduction

Global supply chains have become longer, more fragmented and more dependent on information exchanged between firms that do not fully trust one another. Limited visibility over where goods are, how they were produced and who has handled them raises costs, delays customs and border processes, and weakens the ability of firms and regulators to detect and correct failures. Blockchain, a distributed ledger that records transactions in a tamper-resistant and jointly verifiable way, has been proposed as a technology that can address these problems by creating a shared, auditable record across supply chain partners (Kshetri, 2018; Saberi et al., 2019; Cole et al., 2019).

The academic and practitioner literatures have produced many conceptual frameworks, case studies and pilot implementations that describe how

blockchain could improve transparency and efficiency (Francisco & Swanson, 2018; Treiblmaier, 2018; Helo & Hao, 2019). Systematic reviews nevertheless point to a shortage of empirical testing, and most existing evidence is drawn from single firms, single industries or perception-based surveys (Wang et al., 2019; Queiroz & Wamba, 2019). Very little is known about whether higher blockchain adoption at the country level is accompanied by better logistics outcomes when the same countries are followed over time.

This paper addresses that gap. It examines two research questions: (1) does blockchain technology adoption improve supply chain transparency, and (2) does it improve supply chain operational efficiency? The analysis uses a balanced panel of 20 economies across seven waves of the World Bank Logistics Performance Index (LPI) from 2007 to 2023 and estimates two-way fixed-effects models that control

for time-invariant country characteristics and for global shocks common to all countries.

The paper contributes in three ways. First, it provides a cross-country, panel-based test of two of the most frequently asserted benefits of blockchain in supply chains. Second, it separates the between-country association, which is where most of the variation lies, from the within-country association, which is the more credible basis for a claim about the effect of adoption. Third, it reports how fragile the estimates are to sample composition and inference method, which is uncommon in this literature and matters for how the findings should be used.

The remainder of the paper is organised as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and empirical strategy. Section 4 reports the results, Section 5 discusses them, and Section 6 concludes.

2. Literature Review and Hypothesis Development

2.1 Blockchain and supply chain transparency

Supply chain transparency refers to the extent to which relevant information about products, processes and partners is available, accurate and shared among stakeholders. Blockchain is argued to raise transparency because entries are time-stamped, cannot be altered retrospectively without consensus, and are visible to permissioned participants, so that provenance and custody can be verified rather than merely asserted (Kshetri, 2018; Francisco & Swanson, 2018). Kamble et al. (2020) study blockchain-enabled traceability in agricultural supply chains and identify the enablers that support end-to-end visibility, while Saberi et al. (2019) link blockchain to improved information sharing and to sustainability objectives, alongside a set of intra-organisational, inter-organisational, technical and external barriers.

Two features of this literature matter for the present study. First, the mechanism runs through information sharing between firms, so benefits should depend on how many partners participate, which is a network rather than a single-firm property. Second, the claimed effect is on the quality

of information available about shipments, which is close to what the LPI tracking-and-tracing dimension measures: the ability to track and trace consignments as reported by logistics professionals (Arvis et al., 2023).

2.2 Blockchain and operational efficiency

The efficiency argument is that a shared ledger reduces reconciliation effort, shortens document processing, limits disputes and enables automation through smart contracts, thereby lowering transaction costs and lead times (Kshetri, 2018; Cole et al., 2019; Helo & Hao, 2019). Min (2019) further argues that improved visibility supports more resilient operations. Treiblmaier (2018) cautions that the performance effects of blockchain are contingent, and that they may be offset by implementation costs, scalability limits and coordination problems. At the country level, efficiency gains would need to be large and widespread enough to shift aggregate indicators such as the overall LPI, which combines customs, infrastructure, shipment arrangement, logistics quality, tracking and tracing, and timeliness (Arvis et al., 2023).

2.3 Cross-country evidence and hypotheses

Country-level studies face an identification problem that case studies do not. Digital capability, income, institutions and logistics performance tend to move together across countries, so a positive cross-sectional correlation between technology adoption and logistics performance does not show that adoption improves performance. Panel methods with country fixed effects address part of this problem by relying only on changes within each country over time. If blockchain adoption improves transparency and efficiency in the way the conceptual literature suggests, countries that increase their adoption more rapidly should experience larger improvements in logistics outcomes than countries that increase adoption less, after accounting for common shocks and income growth. This reasoning leads to the following hypotheses:

H1: Blockchain technology adoption has a significant positive effect on supply chain transparency.

H2: Blockchain technology adoption has a significant positive effect on supply chain operational efficiency.

3. Data and Methodology

3.1 Sample and data sources

The sample is a balanced panel of 20 economies observed in the seven LPI survey waves (2007, 2010, 2012, 2014, 2016, 2018 and 2023), giving 140

3.2 Variables

Table 1. Variable definitions and sources

Variable	Measure	Source
Transparency (SCT)	LPI tracking and tracing score, scale 1–5 (higher = better)	World Bank LPI (LP.LPI.TRAC.XQ)
Efficiency (OE)	LPI overall score, scale 1–5 (higher = better)	World Bank LPI (LP.LPI.OVRL.XQ)
Blockchain Adoption Index (BAI)	Composite index scaled 0–1, built from internet users (% of population), secure internet servers (per million people), R&D expenditure (% of GDP) and high-technology exports (% of manufactured exports) [insert normalisation and weighting]	WDI (IT.NET.USER.ZS, IT.NET.SECR.P6, GB.XPD.RSDV.GD.ZS, TX.VAL.TECH.MF.ZS)
GDP per capita (GDP)	GDP per capita, constant 2015 US\$, entered in natural logarithms	WDI (NY.GDP.PCAP.KD)

Note: The LPI is based on a worldwide survey of freight forwarders and express carriers, and the scores are therefore perception-based.

Transparency is proxied by the LPI tracking-and-tracing dimension, which records how easily consignments can be followed and located. Operational efficiency is proxied by the overall LPI score. The overall score includes tracking and tracing as one of its six components, so the two dependent variables are correlated by construction; they are therefore analysed in separate models rather than treated as independent tests. GDP per capita is used as the control variable because income is the most obvious common driver of both technology adoption and logistics performance, and is entered in logarithms to reduce skewness.

No direct, internationally comparable measure of blockchain deployment exists for the full period. The BAI is therefore a composite proxy that captures the digital and technological base on which

country-year observations. Eleven economies are in Asia (China, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, Thailand and Vietnam) and nine are elsewhere (Argentina, Australia, Brazil, Egypt, Germany, Nigeria, South Africa, the United Kingdom and the United States). Logistics outcomes come from the World Bank Logistics Performance Index, and the adoption and control variables come from the World Bank World Development Indicators (WDI). Because the LPI is published in survey waves, all variables are measured in those wave years.

blockchain adoption depends. This is a limitation of the study, and it is discussed in Section 5.

3.3 Empirical model

The baseline is a two-way fixed-effects panel model estimated separately for each outcome:

$$SCT_{it} = \alpha_i + \lambda_t + \beta_1 BAI_{it} + \beta_2 \ln GDP_{it} + \varepsilon_{it} \quad (1)$$

$$OE_{it} = \alpha_i + \lambda_t + \beta_1 BAI_{it} + \beta_2 \ln GDP_{it} + \varepsilon_{it} \quad (2)$$

where i indexes countries and t indexes survey waves, α_i are country fixed effects that absorb all time-invariant differences between countries, λ_t are wave fixed effects that absorb shocks and trends common to all countries, and ε_{it} is the error term. Hypotheses H1 and H2 are supported if β_1 is positive and statistically significant.

3.4 Estimation and inference

The choice of fixed effects over pooled estimation is supported by F-tests for the joint significance of the country effects (transparency: $F(19, 112) = 11.60$; efficiency: $F(19, 112) = 25.14$; both $p < 0.001$). Standard errors are clustered by country to allow for arbitrary serial correlation and heteroskedasticity within countries, with the usual small-sample correction and t -distribution with 19 degrees of freedom (Cameron & Miller, 2015). Because 20 clusters is a small number, the baseline p -values are cross-checked with a wild cluster bootstrap that imposes the null hypothesis (Rademacher weights,

1,999 replications; Cameron et al., 2008). Pooled OLS with wave dummies is reported as a benchmark. All p -values are two-tailed.

Robustness is assessed by (i) entering GDP per capita in levels, (ii) dropping the wave fixed effects, (iii) excluding the 2023 wave, (iv) restricting the sample to Asian economies, (v) excluding one country at a time, and (vi) excluding Argentina, which the leave-one-out exercise identifies as the most influential country. Specifications (v) and (vi) were added after inspecting the baseline results and are therefore exploratory.

4. Results

4.1 Descriptive statistics

Table 2. Descriptive statistics (N = 140; 20 countries $\times$ 7 waves)

Variable	Mean	SD	Min	Max	Within SD	Between SD
Transparency (SCT)	3.530	0.494	2.347	4.400	0.162	0.478
Efficiency (OE)	3.453	0.478	2.371	4.300	0.126	0.471
BAI	0.461	0.191	0.099	0.909	0.106	0.162
GDP per capita (US\$)	21,443	20,727	1,069	65,977	—	—
Ln GDP per capita	9.328	1.240	6.975	11.097	0.137	1.260

Note: Within SD is the standard deviation of deviations from country means; Between SD is the standard deviation of country means.

The average BAI rises steadily from 0.33 in 2007 to 0.64 in 2023, while the average tracking-and-tracing score moves from 3.43 to 3.63 and the average overall LPI from 3.36 to 3.52. Most of the variation in the outcomes is between countries: the between-country standard deviation of the tracking-and-

tracing score is 0.48, compared with a within-country standard deviation of 0.16. Log GDP per capita shows the same pattern (between 1.26, within 0.14). The fixed-effects estimates therefore rely on the much smaller within-country variation, which has implications for statistical precision.

4.2 Correlations

Table 3. Pearson correlations (pooled sample)

	1	2	3	4
1. Transparency (SCT)	1.00			
2. Efficiency (OE)	0.97	1.00		
3. BAI	0.74	0.73	1.00	
4. Ln GDP per capita	0.84	0.84	0.81	1.00

Note: The variance inflation factor for BAI and log GDP per capita is 2.87, which indicates that multicollinearity is not a serious concern in the baseline models.

The BAI correlates strongly with both outcomes ($\rho = 0.74$ with transparency and 0.73 with efficiency). It correlates even more strongly with log GDP per

capita ($\rho = 0.81$), and log GDP per capita is itself highly correlated with both outcomes ($\rho = 0.84$). The raw correlations therefore cannot distinguish an effect of adoption from an effect of development.

4.3 Main results

Table 4. Effect of blockchain adoption on transparency and efficiency

	(1) Pooled OLS	(2) Two-way FE	(3) Pooled OLS	(4) Two-way FE
	<i>Transparency</i>	<i>Transparency</i>	<i>Efficiency</i>	<i>Efficiency</i>
BAI	1.059 (0.624)	−0.031 (0.433)	1.064 (0.676)	−0.059 (0.427)
Ln GDP per capita	0.210** (0.076)	0.398*** (0.097)	0.197** (0.085)	0.439*** (0.093)
Country fixed effects	No	Yes	No	Yes
Wave effects	Yes	Yes	Yes	Yes
Observations	140	140	140	140
Clusters (countries)	20	20	20	20
R ² (pooled) / within R ² (FE)	0.736	0.055	0.730	0.115

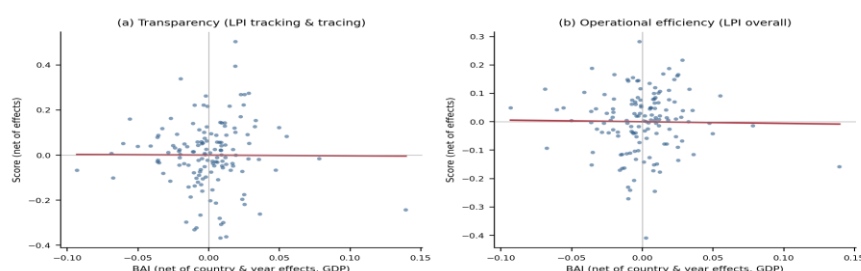
Note: Country-clustered standard errors in parentheses. Pooled models include wave dummies (coefficients not shown). * $p < 0.01$, $p < 0.05$, $p < 0.1$ (two-tailed, t^* distribution with 19 df).

In the pooled specifications, the BAI has a positive coefficient for both transparency ($\beta = 1.059$, $p = 0.106$) and efficiency ($\beta = 1.064$, $p = 0.132$), but neither is statistically significant at the 5% level once standard errors are clustered by country. In contrast, log GDP per capita is significant in the pooled models for both outcomes.

The two-way fixed-effects results are the baseline test of H1 and H2. For transparency, the BAI

coefficient is -0.031 ($SE = 0.433$, $p = 0.945$; 95% CI -0.94 to 0.88), and for efficiency it is -0.059 ($SE = 0.427$, $p = 0.891$; 95% CI -0.95 to 0.83). The wild cluster bootstrap p -values are 0.962 and 0.992, respectively, which agrees with the analytical inference. Within countries, log GDP per capita remains a strong and significant predictor of both outcomes ($\beta = 0.40$ for transparency and 0.44 for efficiency, both $p < 0.001$). Figure 1 shows the partial relationships graphically.

Figure 1. Partial association between BAI and logistics outcomes (two-way fixed-effects, net of log GDP per capita)



Note: Each point is a country-wave observation after removing country and wave means and the linear effect of log GDP per capita. The line is the fixed-effects slope.

4.4 Robustness and sensitivity

Table 5. Robustness of the BAI coefficient

Specification	Transparency (SCT)			Efficiency (OE)			N
	β	SE	p	β	SE	p	
Baseline: two-way FE (Table 4)	−0.031	(0.433)	0.945	−0.059	(0.427)	0.891	140
GDP per capita in levels (US\$ 000)	−0.119	(0.661)	0.858	−0.278	(0.730)	0.708	140

Country FE only (no wave effects)	0.024	(0.141)	0.865	-0.098	(0.160)	0.549	140
Excluding 2023 wave	0.897*	(0.486)	0.080	0.420	(0.578)	0.476	120
Asian economies only	0.910	(0.545)	0.126	0.556	(0.385)	0.179	77
Excluding Argentina	0.796	(0.550)	0.165	0.898***	(0.274)	0.004	133
Excluding Argentina and 2023	1.511*	(0.829)	0.085	1.485**	(0.528)	0.012	114
Leave-one-country-out range of β	[-0.18, 0.80]			[-0.15, 0.90]			133
Wild cluster bootstrap p-value (baseline)			0.962			0.992	140

Note: All models include ln GDP per capita (except the levels specification) and country-clustered standard errors. Rows below the baseline are robustness or exploratory checks; $p < 0.1$, $p < 0.05$, $p < 0.01$. **The Asian subsample has 11 clusters, so inference there is less reliable**

The baseline null result is stable across the specifications that alter the functional form of the control variable or the treatment of time effects (rows 2 and 3). It is not stable across sample definitions. Excluding the 2023 wave changes the transparency coefficient to 0.90 ($p = 0.08$) and the efficiency coefficient to 0.42 ($p = 0.48$), and the Asian subsample gives positive but imprecise estimates. The leave-one-out exercise shows that a single country, Argentina, drives most of the movement: without it the transparency coefficient is 0.80 ($p = 0.16$) and the efficiency coefficient is 0.90 ($p = 0.004$), which is statistically significant. Argentina's BAI rose from 0.14 to 0.68 over the sample period while its LPI scores stagnated and then declined, so it is a strong counter-example to the hypothesised relationship. Dropping both Argentina and the 2023 wave raises the efficiency coefficient to 1.48 ($p = 0.012$).

These additional specifications were chosen after seeing the baseline results, and several were run on the same data. They should be read as evidence about the fragility of the baseline conclusion and not as a replacement estimate. In particular, removing a country because it weakens the result would not be a defensible basis for the headline finding.

4.5 Assessment of hypotheses

H1 (transparency): not supported. The within-country effect of the BAI on the LPI tracking-and-tracing score is statistically indistinguishable from zero in the baseline model ($p = 0.94$), and the confidence interval is wide. **H2 (efficiency): not supported in the baseline.** The efficiency

coefficient is also indistinguishable from zero ($p = 0.89$), although it becomes positive and significant when Argentina is excluded. Because that exclusion was not planned, the baseline result is treated as the primary finding.

5. Discussion

The main finding is a contrast between the between-country and within-country evidence. Countries with higher BAI scores tend to have better tracking and tracing and better overall logistics performance, but this association disappears when each country is compared only with itself over time. This pattern is what one would expect if the BAI mostly reflects long-run national development, which also drives logistics quality, and does not reflect a distinct effect of adoption. The large and significant coefficient on log GDP per capita in the fixed-effects models is consistent with this reading.

Several explanations for the absence of a within-country effect deserve consideration. The first is measurement. The BAI is built from indicators of digital infrastructure and technological capacity, and these are necessary conditions for blockchain adoption, but they are not measures of blockchain deployment in supply chains. A country can score highly on the index without having any material blockchain activity in logistics, in which case a null effect says little about the technology itself. The second is timing. Blockchain pilots in supply chains became prominent after 2016, and their effects on aggregate indicators are likely to appear only after network participation reaches a critical mass, so the periods in which adoption could plausibly matter are

few. The third is the outcome measure. The LPI is a perception-based survey index published in waves, with limited year-to-year variation within countries (within-country SD of only 0.16 points for tracking and tracing), which makes it a coarse instrument for detecting gradual technology effects.

The fourth explanation is statistical power. With 20 countries and small within-country variation, the confidence intervals are wide: for the baseline transparency model they range from -0.94 to 0.88 . Because the BAI is scaled from 0 to 1, a 0.1-point increase in the index corresponds to a change in the LPI of roughly -0.09 to 0.09 points at the limits of that interval. The evidence therefore rules out very large effects, but it cannot exclude modest positive or negative ones. The null result is best described as inconclusive and not as proof of no effect.

The sensitivity to Argentina and to the 2023 wave suggests that effects, if present, may be heterogeneous. A country in which digital capability rose sharply while logistics performance stagnated is consistent with adoption being insufficient without complementary conditions such as macroeconomic stability, customs efficiency, or regulatory support. The present data cannot test this, since the analysis has no direct measure of those conditions, but it suggests examining conditional effects, in which the returns to adoption depend on country-level enabling factors, as a natural next step.

The findings have two practical implications. For policymakers, they caution against expecting national investments in digital infrastructure to raise logistics performance by themselves, and they support pairing such investments with complementary reforms. For researchers, they show that studies which rely on cross-sectional correlations between technology indicators and logistics outcomes are likely to overstate the effect of the technology, because the correlation is largely driven by income and institutional differences between countries.

6. Conclusion

This paper examined whether blockchain adoption improves supply chain transparency and operational efficiency using a balanced panel of 20 economies

and seven LPI waves from 2007 to 2023. The pooled data show a positive but statistically insignificant association, and the two-way fixed-effects estimates, which are the more credible test of an adoption effect, are close to zero for both transparency ($\beta = -0.03$) and efficiency ($\beta = -0.06$). Hypotheses H1 and H2 are therefore not supported in the baseline. The estimates are imprecise and depend on the inclusion of Argentina and the 2023 wave, so the evidence is inconclusive and not a rejection of the potential benefits of blockchain.

The study has several limitations. The BAI is a proxy for technological capacity, not a measure of realised blockchain deployment. Tracking and tracing captures only one aspect of transparency, and the overall LPI is a broad composite that only partly reflects the processes blockchain is expected to influence. The sample of 20 economies is small and mixes Asian and non-Asian countries, and the seven survey waves are unevenly spaced, which prevents a study of lagged effects. The models estimate associations under the fixed-effects assumption and do not address time-varying omitted factors or reverse causality.

Future research should (i) construct adoption measures from direct data, such as blockchain patents, enterprise platform deployments, national blockchain strategies or trade-facilitation initiatives; (ii) use disaggregated logistics outcomes, including the LPI customs and timeliness dimensions, alongside transparency-specific measures; (iii) expand the panel to more countries and to annual data; (iv) study traceability as a separate outcome; and (v) test whether technological readiness and regulatory quality condition the returns to adoption.

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