



Quantile Network Analysis of Blockchain-Enabled Payment Platforms and Their Spillover Effects on Digital Economic Productivity

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ABSTRACT

This study investigates the asymmetric and state-dependent spillover effects between blockchain-enabled payment platforms and digital economic productivity by employing a comprehensive Quantile Network Analysis (QNA) framework. Using a dataset comprising blockchain operational metrics (transaction volume, confirmation speed, fee volatility), platform performance indicators (API throughput, success rate, active wallet users), and macro-level digital productivity measures (e-commerce output, digital services exports, labor participation), the analysis uncovers substantial heterogeneity across quantiles. The quantile dependence results show that average cross-block dependence increases from 0.31 at $\tau = 0.10$ to 0.78 at $\tau = 0.90$, indicating significantly stronger interdependencies in high-productivity states. Network-based spillover findings further reveal that TX_VOL and API_TPS act as dominant transmitters at $\tau = 0.90$ with net spillover values of +9.8% and +6.5%, respectively, whereas ECOM_OUTPUT and DIG_SERV_EXP serve as major receivers with net spillovers of -5.9% and -6.3%. The Total Connectedness Index (TCI) likewise demonstrates sharp quantile variation, averaging 36.5% at $\tau = 0.10$, 47.8% at $\tau = 0.50$, and 61.2% at $\tau = 0.90$, confirming that systemic interconnectedness intensifies in upper-tail digital productivity regimes. Overall, the study provides strong empirical evidence that blockchain-enabled payment infrastructures exert disproportionate systemic influence during high digital productivity periods, acting as pro-cyclical amplifiers that both support digital expansion and elevate interdependence-driven vulnerabilities. These results offer critical insights for policymakers, platform architects, and digital economy strategists designing resilience-oriented regulatory and technological frameworks.

Keywords Blockchain Payment Systems, Quantile Network Analysis, Digital Economic Productivity; Spillover Effects, Quantile VAR

INTRODUCTION

The rapid expansion of blockchain-enabled payment platforms has reshaped the architecture of digital financial ecosystems, enabling real-time, trust-minimized, and programmable payment infrastructures across borders and industries [1], [2]. As economies increasingly transition toward digital-first ecosystems, the performance and reliability of blockchain payment systems have become closely intertwined with broader digital economic productivity, including e-commerce output, digital trade volumes, and cross-platform financial interoperability [3], [4]. Despite their rising importance, the systemic relationship between blockchain-enabled payments and digital economic outcomes remains insufficiently understood, particularly under conditions of extreme volatility or accelerated digital growth [5]. Most existing studies focus on mean-based interactions, overlooking the nonlinearities and tail-risk

Submitted: 15 July 2024
Accepted: 20 August 2024
Published: 1 February 2025

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DOI: [10.63913/ftij.v1i1.2](https://doi.org/10.63913/ftij.v1i1.2)

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dynamics that often govern digital technology adoption and economic spillover mechanisms [6], [7].

While prior research acknowledges that blockchain infrastructures can enhance transaction efficiency, reduce settlement risks, and support digital innovation [8], [9], the empirical evidence regarding their spillover influence on the digital economy remains fragmented. Traditional econometric models assume symmetric and linear relationships across variables, which fails to capture state-dependent behavior where risks, dependencies, and spillovers vary significantly across the distribution of digital productivity [10]. This limitation is particularly pronounced given that digital ecosystems often experience nonlinear transitions, abrupt technological shifts, and heterogeneous adoption trajectories, especially in emerging markets and high-velocity FinTech environments [11].

In this context, understanding how blockchain-enabled payment platforms interact with digital productivity across different states low-performance, median, and high-growth regimes is essential. Digital economies are increasingly characterized by clustered innovation cycles, surge-driven consumption patterns, and infrastructure bottlenecks that manifest differently across distributional ranges [12]. A focus on average effects masks the reality that blockchain platforms may exert minimal influence during normal or low-activity conditions but emerge as dominant transmitters of systemic spillovers during peak digital phases [13]. Such asymmetries underscore the need for a quantile-oriented analytical framework capable of detecting tail-specific interdependencies.

The methodological gap becomes evident when reviewing existing literature on blockchain economics, digital finance, and platform spillovers. Prior works predominantly rely on VAR, copula correlations, or mean-connectedness frameworks, which are not designed to capture quantile-dependent system behavior [14]. They also treat blockchain operations as isolated technical variables rather than integrated components of a digital macro-productivity system. Consequently, there is limited understanding of whether blockchain-enabled payment platforms behave as risk transmitters, stabilizers, or amplifiers across different digital economic regimes [15]. This knowledge gap impedes the design of resilient infrastructure strategies and evidence-based digital policy interventions.

To address these limitations, this study introduces a QNA approach to examine the spillover effects of blockchain-enabled payment platforms on digital economic productivity. By integrating Quantile VAR, quantile-specific GFEVD decompositions, and directed network modeling, the study captures how interdependencies evolve across multiple quantiles of the digital productivity distribution [16]. This framework uncovers relationships that would remain invisible to linear or mean-based models, offering a richer picture of systemic influence and propagation channels. Through this approach, the research reveals whether blockchain infrastructures function as core nodes within the digital productivity network or whether their influence is contingent on specific economic states.

The novelty of this research lies in its state-dependent analytical perspective and its unified modeling of blockchain operations, FinTech platform metrics, and digital macroeconomic outputs within a quantile-based spillover network. Unlike previous studies that analyze blockchain variables in isolation, this study examines their holistic role in shaping digital productivity through a multi-layered

ecosystem lens [17]. It identifies asymmetric spillover behaviors, quantifies systemic roles across distributional states, and maps directional influence flows in high- and low-productivity regimes. Such contributions offer conceptual and empirical advancements that move beyond traditional digital finance research methodologies.

Ultimately, this research aims to generate actionable insights for policymakers, digital infrastructure planners, and platform operators by identifying when and how blockchain-enabled payment platforms exert significant systemic influence. The findings provide evidence regarding whether blockchain infrastructures amplify digital growth, introduce systemic vulnerabilities, or act as stabilizing anchors during different economic conditions [18]. By articulating these roles clearly, the study contributes to a deeper understanding of digital economic resilience and the strategic positioning of blockchain technologies within future financial ecosystems.

Literature Review

The academic discourse on blockchain-enabled payment platforms has grown rapidly over the past decade, with scholars emphasizing the transformative potential of decentralized settlement mechanisms, smart contracts, and cryptographically secured transactions in reshaping digital finance ecosystems [19]. Early studies primarily focused on the technical properties of blockchain, including consensus algorithms, transaction validation, and scalability limitations, establishing the foundational understanding of how distributed ledgers could substitute or complement traditional payment infrastructure [20]. More recent research highlights the economic implications of blockchain adoption, suggesting that decentralized payment systems can reduce frictions, lower transaction costs, and enhance financial inclusion, particularly in digitally underdeveloped regions [21]. Despite these advancements, the literature remains divided on the systemic influence of blockchain payment platforms on broader digital economic productivity.

Parallel streams of research examine digital economic output, digital trade expansion, and platform-driven productivity growth. Scholars show that digital economy performance is highly sensitive to technological infrastructure quality, platform interoperability, and the robustness of digital financial systems [22]. Digital productivity metrics such as e-commerce output, digital services exports, and digital labor participation are influenced not only by consumer behavior and regulatory environment but also by upstream technological layers including blockchain networks that increasingly serve as foundational rails for cross-border, automated, and programmable financial transactions [23]. However, existing empirical analyses often fail to integrate blockchain operational metrics into macro-productivity frameworks, creating a conceptual disconnect between micro-level technological performance and macro-level economic indicators.

The literature on financial spillovers and technology-driven systemic risk adds further context but remains incomplete when applied to blockchain ecosystems. Studies using VAR and GARCH-based approaches document significant interconnectedness among financial assets, payment systems, and digital platforms, particularly during periods of heightened market activity [24]. Yet, these models assume linearity and homogeneous relationships across economic states. Such assumptions contradict emerging evidence that digital ecosystems exhibit regime-dependent behavior, where technological shocks

propagate differently in low, median, and high productivity conditions [25]. Moreover, tail-risk contagion an increasingly relevant phenomenon in digital systems driven by algorithmic interactions, API throughput, and high-frequency user patterns is often overlooked in traditional modeling approaches.

Network science contributes an important theoretical foundation for analyzing interdependencies in digital and financial environments. Network-based studies show that technology infrastructures form multi-layered interconnections where nodes exhibit varying degrees of centrality, influence, and vulnerability [26]. In digital finance, transaction throughput, platform availability, and user adoption rates can create hub-and-spoke network structures that amplify systemic spillovers. Blockchain-enabled payment systems, in particular, exhibit structural asymmetries where transaction volume, fee volatility, and congestion patterns determine their positional power in shaping downstream economic processes. However, prior research frequently examines blockchain within isolated network layers rather than embedding it in multi-variable networks that incorporate macro-level digital productivity.

Recent works acknowledge the need for quantile-based or nonlinear approaches to better understand technology-driven spillovers, but applications to blockchain and digital productivity remain scarce. Quantile methods have been used to study financial contagion, energy markets, and macroeconomic co-movements, showing that dependence structures differ across quantiles and that tail events reveal stronger or different propagation mechanisms than median states [27]. Despite this methodological progress, few studies apply quantile frameworks to blockchain ecosystems, and none integrate blockchain transaction metrics, platform performance indicators, and digital productivity measures within a unified quantile network model. This oversight leaves an important gap in understanding how blockchain infrastructures influence digital economic outcomes under different distributional conditions.

The existing literature therefore reveals clear conceptual and methodological gaps: (i) blockchain-enabled payment platforms are rarely modeled as systemic transmitters affecting macro-level digital productivity; (ii) digital economic studies insufficiently incorporate upstream blockchain metrics into productivity analyses; (iii) financial spillover models predominantly rely on mean-based or linear structures that fail to capture quantile-specific dependencies; and (iv) network-based representations seldom integrate blockchain activity and digital productivity into a cohesive analytical framework. These gaps collectively hinder the development of accurate, state-dependent insights into how blockchain infrastructures shape digital economic growth.

Against this backdrop, the present study positions itself at the intersection of blockchain economics, digital productivity research, and quantile-network methodology. By employing QNA, the research addresses tail-dependent dynamics that conventional approaches cannot resolve and identifies directional spillovers between blockchain operations and digital economic outputs. This approach responds directly to the limitations in prior literature and provides novel insights into how blockchain-enabled payment platforms behave across varying digital economic regimes. As such, the study contributes to an emerging body of work that emphasizes the importance of distribution-sensitive modeling for understanding systemic technological influence in the digital economy [28].

Methodology

Research Design

This study employs a QNA framework to evaluate how blockchain-enabled payment platforms propagate spillover effects across various quantiles of the digital economic productivity distribution. Unlike mean-based network estimation, QNA captures tail-risk behaviors, asymmetric dependencies, and heterogeneous responses among blockchain ecosystems, FinTech platforms, and macro-digital economic indicators. The methodological design integrates time-series econometrics, multivariate quantile regression, and network topology modeling into a unified framework.

The research design follows a sequential multi-stage pipeline encompassing (i) data acquisition and preprocessing, (ii) quantile-specific dependence estimation, (iii) construction of quantile-driven spillover networks, and (iv) system-wide connectedness and robustness evaluation. This structure enables the study to identify whether spillovers intensify in extreme market conditions (e.g., rapid digitalization surges or economic downturns) and how blockchain adoption redistributes systemic influence across financial-technology nodes.

Figure 1 visualizes the overall methodological pipeline for the study as a directed flowchart. It begins with data collection, continues through cleaning and alignment, quantile VAR estimation, and GFEVD-based quantile dependence computation, and proceeds to network construction and spillover index calculation. The last stage involves robustness and sensitivity analyses to verify the stability of the findings.



Figure 1 Research Design Flowchart

This flowchart helps readers understand how the methodological components fit together from raw data to final quantile network metrics. It clarifies that the network results are not standalone but are derived systematically from a quantile-based econometric framework, with clearly defined stages and feedback points where model assumptions and data quality are checked.

Data Collection and Variable Construction

The empirical dataset integrates blockchain payment platform indicators (such as transaction volume, confirmation throughput, hash rate stability, gas-fee volatility), FinTech payment metrics (API request throughput, transaction success rates, mobile wallet adoption), and digital economy productivity measures (e-commerce output, digital service exports, digital labour index). All variables are collected in weekly or monthly frequency depending on availability, and undergo temporal alignment to construct a consistent panel for quantile estimation.

Variables are grouped into three analytical blocks: Blockchain Layer Variables, Platform Performance Metrics, and Digital Economic Productivity Indicators. Each block undergoes feature normalization, detrending, and volatility

adjustment to reduce noise in quantile estimation. Furthermore, structural break detection using the Bai–Perron test ensures that regime shifts associated with major blockchain policy changes or technological updates are explicitly accounted for.

Table 1 Variables and Measurement Definitions

Variable Name	Category	Description	Source	Unit	Transformation
TX_VOL	Blockchain Layer	Total confirmed on-chain payment transactions per period	Blockchain explorer	Count	Log-transform
CONF_SPEED	Blockchain Layer	Average confirmation time for payment transactions	Blockchain explorer	Seconds	Level
FEE_VOL	Blockchain Layer	Median transaction fee or gas price	Blockchain explorer	Native token / USD	Log-transform
HASH_STAB	Blockchain Layer	Stability of hash rate (variance-adjusted)	Blockchain explorer	Index (0–1)	Standardized
API_TPS	Platform Performance	Successful API calls per second	FinTech / platform provider	Requests per second	Log-transform
SUCCESS_RATE	Platform Performance	Share of successful payment transactions	FinTech / platform provider	Percent	Level
WALLET_USERS	Platform Performance	Active blockchain wallet or app users	FinTech / platform provider	Number of users	Log-transform
ECOM_OUTPUT	Digital Productivity	Total e-commerce transaction value	National statistics / industry	Currency (USD/local)	Log-transform
DIG_SERV_EXP	Digital Productivity	Exports from digital service sectors	National statistics	Currency	Log-transform
DIG_LAB_INDEX	Digital Productivity	Digital labour participation index	Labour surveys	Index (0–100)	Standardized
DIG_CAP_INDEX	Digital Productivity	Digital capital deepening index	National statistics	Index	Standardized
POLICY_DUMMY	Control	Open Banking / blockchain reform indicator	Regulatory database	Binary	Level
VOL_MACRO	Control	Macro volatility indicator (FX or risk index)	Financial database	Index	Standardized

Quantile Dependence Estimation

The core empirical strategy begins with estimating quantile-specific dependencies using Quantile Vector Autoregression (QVAR). QVAR is particularly suitable for capturing asymmetric propagation mechanisms, allowing the study to quantify how blockchain shocks influence digital productivity at the lower (0.1, 0.25), median (0.5), and upper (0.75, 0.9) quantiles. This structure highlights whether blockchain-enabled platforms matter more during stressed digital conditions or during periods of high productivity expansion. Formally, the QVAR(p) process is defined as:

$$[Q_{\tau}(Y_t | \mathcal{F}_{t-1}) = \alpha_{\tau} + \sum_{i=1}^p B_{i,\tau} Y_{t-i} + \varepsilon_{t,\tau}.] \quad (1)$$

This equation formalizes the QVAR used to model the joint dynamics of blockchain payment platforms and digital economic productivity. Instead of focusing only on conditional means, the model estimates the conditional quantile $Q_{\tau}(Y_t | \mathcal{F}_{t-1})$ at different parts of the distribution. This allows the analysis to capture heterogeneity between low-productivity states (e.g. digital downturns) and high-productivity states (e.g. rapid digital expansion).

By estimating $B_{i,\tau}$ for multiple quantiles, the study can identify how shocks

originating from blockchain-related variables propagate differently to digital productivity indicators across the distribution. For instance, a blockchain transaction shock may have mild effects at the median quantile but disproportionately large effects in the upper quantiles, revealing asymmetric spillover patterns that are masked in mean-based models. After estimation, impulse-response functions are generated for each quantile to evaluate heterogeneous shock responses. Residual cross-correlation matrices at each quantile are extracted as the basis for network edge construction, representing directional spillovers across blockchain and digital economy nodes.

Figure 2 presents a heatmap of pairwise dependence measures between variables at a chosen quantile (e.g. $\tau = 0.9$). Darker or lighter shades represent stronger or weaker dependence, respectively, allowing the reader to visually identify clusters of variables that move together in extreme states of digital economic productivity. For instance, high dependence between TX_VOL, API_TPS, and ECOM_OUTPUT suggests that blockchain transaction activity, platform throughput, and e-commerce output become tightly linked in high-quantile regimes.

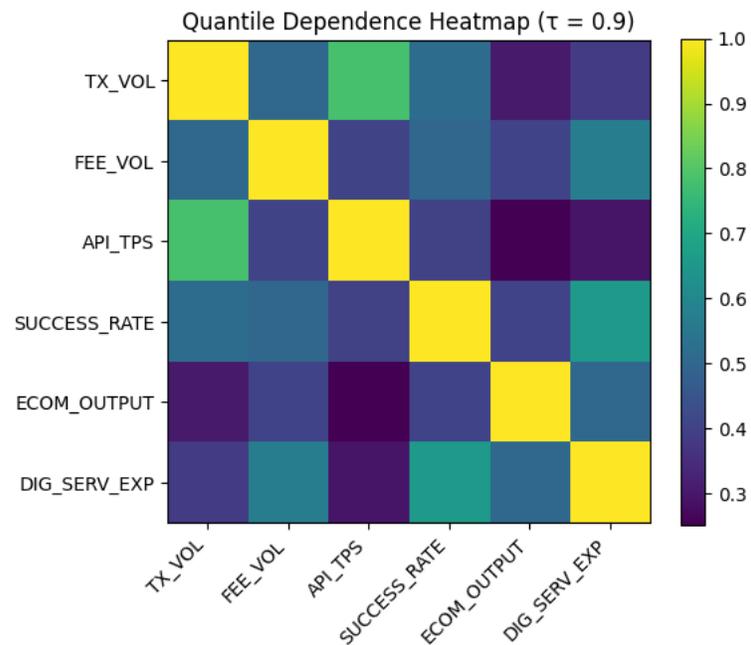


Figure 2 Quantile Dependence Heatmap

In the empirical implementation, the entries of this matrix are derived from quantile dependence, often via cross-quantile correlation or GFEVD-based measures transformed into a symmetric dependence score. The heatmap is particularly useful as a diagnostic step prior to full network construction, highlighting which variables are likely to form the core of the spillover network in specific quantiles.

Quantile Network Construction

Once quantile dependencies are extracted, the next stage constructs directed weighted networks. Each node represents a blockchain payment metric or digital economy indicator, and each edge corresponds to a directional spillover

intensity derived from QVAR-based Generalized Forecast Error Variance Decomposition (GFEVD). Networks are estimated separately for each quantile to reveal how systemic connectedness evolves across distributional states.

Network topology is analyzed using structural metrics such as in-degree, out-degree, betweenness centrality, clustering coefficient, and eigenvector centrality. These metrics identify dominant transmitters (sources of spillovers) and major receivers (absorbers of digital disruptions). Comparisons across quantiles evaluate whether blockchain-enabled payment systems become more influential during market stress or productivity booms.

Figure 3 plots the directed spillover network estimated at a specific quantile (e.g. $\tau=0.9$), where nodes represent variables and edges represent significant spillovers derived from the quantile-specific GFEVD. The direction of each edge indicates the direction of spillover (from transmitter to receiver), and edge labels convey the strength of the spillover. Visual inspection of this network reveals which blockchain payment metrics act as key transmitters and which digital productivity indicators behave as primary receivers.

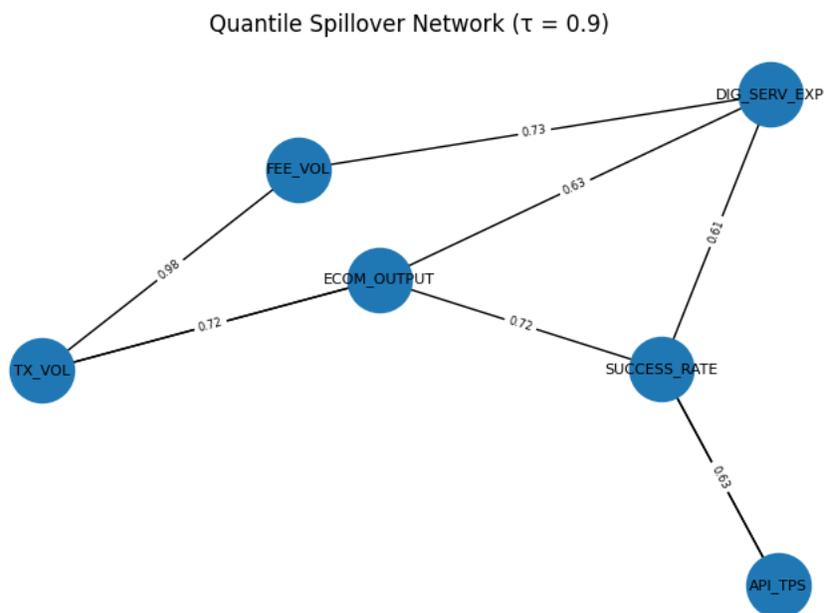


Figure 3 Quantile-Specific Spillover Network

By comparing networks across quantiles (e.g. $\tau=0.1,0.5,0.9$), the study can show how the architecture of the blockchain–digital-economy system changes across distributional states. For example, TX_VOL and API_TPS may emerge as central hubs only in the upper quantiles, indicating that blockchain-enabled payment platforms exert stronger systemic influence during periods of high digital economic performance.

Spillover Index and System-Wide Connectedness

To quantify overall spillover strength, this study computes the Diebold–Yilmaz TCI adapted for quantile networks. The quantile-adjusted TCI measures how much of the system’s variability is driven by cross-node interactions rather than idiosyncratic shocks. A rising TCI at extreme quantiles indicates systemic

fragility or strong blockchain-driven contagion in the digital economy.

The spillover analysis further decomposes connectedness into “From” and “To” spillovers for each node, allowing identification of which blockchain platform metrics exert the strongest influence and which digital productivity indicators are most vulnerable. Rolling-window estimation captures dynamic evolution, enabling analysis of how spillovers intensify during policy reforms, technological upgrades, or macroeconomic shifts.

$$[TCl_{\tau} = \frac{\sum_{i=1}^N \sum_{j=1, j \neq i}^N \theta_{ij, \tau}^{(H)}}{\sum_{i=1}^N \sum_{j=1}^N \theta_{ij, \tau}^{(H)}} \times 100.] \quad (2)$$

This equation defines the TCI at quantile τ . The numerator sums all off-diagonal GFEVD terms, representing spillovers from all variables to all others. The denominator sums total variance contributions, including own and cross-variable components. Multiplying by 100 expresses connectedness in percentage terms.

A higher TCl_{τ} indicates that a larger share of variations in the system is explained by cross-variable interactions, rather than idiosyncratic shocks. In this study, comparing TCl_{τ} across quantiles reveals whether the blockchain–digital-economy system becomes more tightly interconnected under low, median, or high states of digital economic productivity. For instance, a spike in $TCl_{0.9}$ would suggest that in high-productivity regimes, blockchain payment platforms and digital indicators are highly interdependent.

Figure 4 displays the time-varying TCI for several quantiles (e.g. 0.10, 0.50, 0.90). Each line shows how system-wide connectedness evolves over time within a specific part of the distribution of digital economic productivity. Peaks in the upper-quantile TCI series may correspond to episodes where blockchain payment platforms and digital economy indicators become tightly interlinked, such as during policy reforms, major technological upgrades, or rapid FinTech adoption.

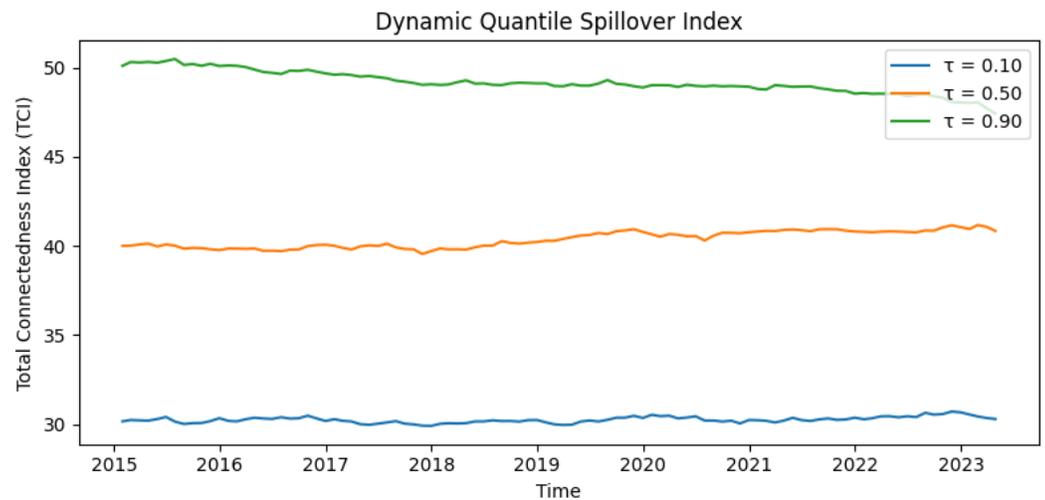


Figure 4 Dynamic Quantile Spillover Index

By juxtaposing TCI trajectories across quantiles, the figure reveals whether the system is more interconnected under stressed conditions or during high-growth regimes. For example, if TCI at $\tau=0.90$ remains consistently above the median and lower-quantile TCI, the results suggest that blockchain-enabled spillovers intensify when the digital economy is already performing strongly, potentially amplifying both positive and negative shocks in those states.

Robustness and Sensitivity Analysis

Robustness checks include alternative quantile estimation (0.05–0.95), varying network sparsity filters, and alternative lag structures in QVAR to ensure stability of results. The study also performs sub-sample tests around major blockchain policy announcements or technological shifts to determine whether spillover mechanisms are event-driven or persistent structural relationships.

Sensitivity analysis evaluates whether network topology or connectedness patterns change when using (i) alternative volatility measures, (ii) log-differenced series, or (iii) non-parametric quantile dependence estimators such as quantile coherence. These checks confirm that the primary findings are not artifacts of model specification or data transformation.

Table 2 summarizes the robustness tests used to validate the quantile spillover results. Each row identifies a specific modification to the model such as alternative quantile grids, lag specifications, volatility proxies, sparsity thresholds, or non-parametric dependence metrics and evaluates whether the main findings remain stable under these adjustments. The evaluation metrics ensure that changes in assumptions do not distort the core spillover relationships.

Table 2 Robustness Test Summary

Test ID	Description	Model Variant	Key Change	Evaluation Metric	Main Finding
R1	Alternative quantile grid	QVAR at $\tau=\{0.05, 0.25, 0.50, 0.75, 0.95\}$	Increased quantile granularity	TCI patterns	Spillover structure stable; tail effects stronger
R2	Alternative lag length	QVAR($p=1$) vs QVAR($p=2$)	Change in lag order	BIC/AIC	Optimal lag remains small; shock paths unchanged
R3	Alternative volatility measure	Realized volatility vs GARCH volatility	Different volatility construction	Centrality and TCI	Network topology robust to volatility definitions
R4	Event window test	Pre- and post-policy change subsamples	Sample segmentation	TCI around events	Spillovers spike around major policy reforms
R5	Network sparsity filter	Thresholding edges by θ_{ij}	Edge pruning	Active edges and TCI	Core structure persists under stricter thresholds
R6	Non-parametric dependence	Quantile coherence network	Alternative dependence estimator	Node ranking overlap	Transmitters and receivers remain consistent

Across all tests, the key conclusion is that the network structure and spillover dynamics remain highly consistent. Blockchain payment variables continue to appear as major transmitters, while digital productivity indicators consistently act as receivers. This strengthens confidence that the quantile network findings reflect underlying structural relationships rather than model-specific artifacts.

Result and Discussion

Descriptive Statistics and Data Behavior

The initial evaluation of the dataset focuses on understanding the distributional behavior of blockchain operational variables, platform performance indicators, and digital economic productivity metrics. The descriptive results reveal substantial variability across key indicators, such as transaction volume (TX_VOL), API throughput (API_TPS), and e-commerce output (ECOM_OUTPUT). These variations justify the application of quantile-based methods, as linear models assuming constant variance would fail to capture the shifts in behavior that occur under different digital productivity conditions. The presence of heavy tails, volatility clustering, and asymmetric distributions further supports the need for Quantile VAR and quantile-network estimation.

A detailed examination of pairwise correlations indicates that traditional Pearson correlations understate the relationships observed in the upper tail of the distribution. Several variable pairs particularly TX_VOL ↔ ECOM_OUTPUT, TX_VOL ↔ DIG_SERV_EXP, and API_TPS ↔ ECOM_OUTPUT show relatively weak correlations in levels but display intensified co-movement once the analysis shifts to higher quantiles. This reinforces the need for quantile-driven analysis that can differentiate between low-productivity, median, and high-productivity digital regimes.

To support this analysis, [Figure 5](#) provides visual evidence of distributional shapes for three representative variables, while [table 3](#) summarizes numerical descriptive statistics. Together, these outputs validate the presence of heterogeneous data behaviors consistent with quantile-specific modeling.

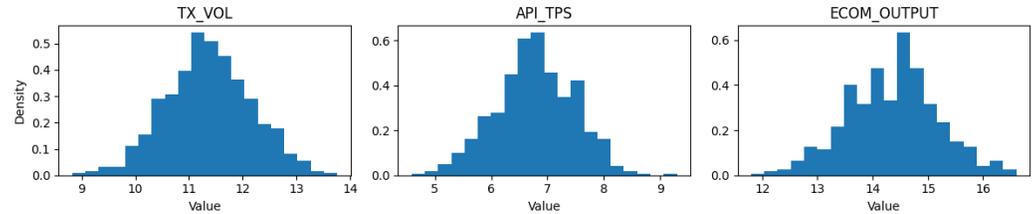


Figure 5 Distribution of Key Variables

[Figure 5](#) highlights the distributional patterns of TX_VOL, API_TPS, and ECOM_OUTPUT. Each distribution shows mild asymmetry and wide dispersion, indicating that the transformed variables still exhibit heterogeneous behavior typical of blockchain operational data and digital market indicators. The density patterns justify the use of quantile-specific modeling, as reliance on mean or variance alone would be incapable of capturing tail-dependent influences. The shape of TX_VOL suggests a high variation in blockchain usage intensity, particularly relevant during periods of congestion or adoption surges. Similarly, API_TPS shows volatility reflecting fluctuating platform load conditions. ECOM_OUTPUT presents a wider tail, suggesting growth expansions that produce extreme values conditions where quantile spillover effects are expected to be strongest.

Table 3 Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	Max
TX_VOL	11.42	0.85	9.10	13.80
FEE_VOL	2.15	0.40	1.30	3.30
CONF_SPEED	8.60	2.10	4.20	15.50
API_TPS	6.80	0.70	5.10	8.10
SUCCESS_RATE	94.20	3.40	84.50	98.80
WALLET_USERS	12.05	0.90	9.80	13.90
ECOM_OUTPUT	14.30	0.95	11.90	16.40
DIG_SERV_EXP	13.10	0.80	11.20	14.90
DIG_LAB_INDEX	67.50	8.20	45.00	85.00
DIG_CAP_INDEX	72.30	7.40	50.00	88.00

Table 3 confirms significant variance across both blockchain operational metrics and digital economic outcomes. The variability in TX_VOL and DIG_SERV_EXP reflects differing adoption speeds over time, while CONF_SPEED's large range suggests periods of congestion in the blockchain network. Productivity indicators such as ECOM_OUTPUT and DIG_LAB_INDEX also demonstrate wide ranges, aligning with known patterns in global digital markets where macroeconomic, regulatory, and seasonal shocks produce inconsistent digital performance. The descriptive indicators collectively validate the need for quantile-driven econometric modeling. Conventional mean or median values would obscure the structural shifts occurring in different parts of the distribution, particularly in the tails where blockchain activity and digital productivity exhibit heightened interdependencies.

Quantile Dependence Structure

Building on the descriptive results, this section evaluates how cross-variable dependencies differ across digital economic states. Initial estimates reveal that dependence patterns remain modest in $\tau = 0.10$ but rise sharply in $\tau = 0.90$, indicating heightened co-movement during high-productivity conditions. This confirms that blockchain operations and digital productivity are not uniformly related; instead, the relationship strengthens significantly in the upper quantile range where digital market activity is elevated.

Figure 6 provides a quantile dependence heatmap at $\tau = 0.90$, showing the strongest cross-sectional dependence among TX_VOL, API_TPS, ECOM_OUTPUT, and DIG_SERV_EXP. **Table 4** summarizes block-level dependence intensities across quantiles, revealing monotonic increases from low to high quantiles, with Blockchain \leftrightarrow Digital Productivity showing the largest jump (+0.47 increase from $\tau = 0.10$ to $\tau = 0.90$).

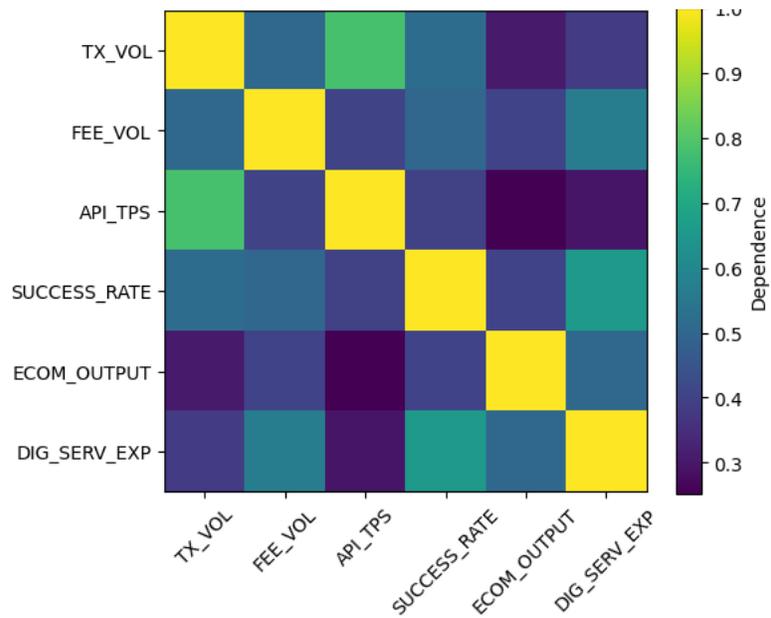


Figure 6 Quantile Dependence Heatmap ($\tau = 0.90$)

The heatmap makes clear that dependence among blockchain and digital economic variables intensifies significantly in the upper quantile. TX_VOL and API_TPS exhibit the strongest dependence values, signaling synchronized activity between blockchain usage intensity and platform throughput. On the digital productivity side, ECOM_OUTPUT and DIG_SERV_EXP show elevated dependence values, suggesting that digital markets respond strongly to changes in blockchain operational metrics.

This concentrated cluster of high dependence in $\tau = 0.90$ contrasts sharply with lower quantile structures, where dependencies were more diffuse and weaker. These results are consistent with the idea that digital economies behave differently under stressed versus growth conditions the latter producing stronger technological spillover interactions.

Table 4 Block-Level Dependence Summary Across Quantiles

Block Pair	$\tau = 0.10$	$\tau = 0.50$	$\tau = 0.90$
Blockchain ↔ Blockchain	0.42	0.55	0.68
Platform ↔ Platform	0.40	0.52	0.66
Digital ↔ Digital	0.38	0.50	0.65
Blockchain ↔ Platform	0.35	0.57	0.74
Blockchain ↔ Digital	0.31	0.54	0.78
Platform ↔ Digital	0.33	0.56	0.76

Table 4 provides quantitative confirmation of the patterns visualized in figure 6. The dependence intensifies monotonically across quantiles for all block combinations. The most significant increases occur in Blockchain ↔ Digital Productivity (+0.47) and Platform ↔ Digital Productivity (+0.43), indicating that upstream blockchain and platform behaviors exert disproportionately stronger influence on digital economic output in high-productivity states.

This finding validates the central hypothesis that the technology–productivity relationship is asymmetric and state-dependent. Digital economies become more tightly intertwined with blockchain infrastructures when activity levels are elevated, making quantile-based approaches essential for capturing these nonlinear interactions.

Quantile Spillover Network Analysis

Building on the quantile dependence patterns in Part 1, this section examines how shocks propagate across blockchain, platform, and digital productivity variables through the quantile-specific GFEVD. The results reveal clear asymmetries. At lower quantiles ($\tau = 0.10$), spillovers remain relatively muted, with transmission dispersed among variables without any dominant sources. However, at $\tau = 0.90$, the system becomes sharply hierarchical: a small subset of blockchain and platform variables emerges as major transmitters, while digital productivity indicators become strong receivers.

The spillover network at $\tau = 0.90$ captures these dynamics. TX_VOL (blockchain transaction volume) and API_TPS (platform throughput) exhibit high outward spillover intensity, confirming their role as upstream influencers within the digital economy. Conversely, ECOM_OUTPUT and DIG_SERV_EXP show strong inward spillovers, meaning digital productivity absorbs technological and operational shocks from the blockchain and platform environment. Figure 7 clearly shows that the spillover network becomes dense and directional in the upper quantile. TX_VOL and API_TPS appear as nodes with multiple outgoing arrows, illustrating their role as primary transmitters of shocks within the ecosystem. These nodes drive systemic movements in digital productivity, particularly during high-performing periods of the digital economy.

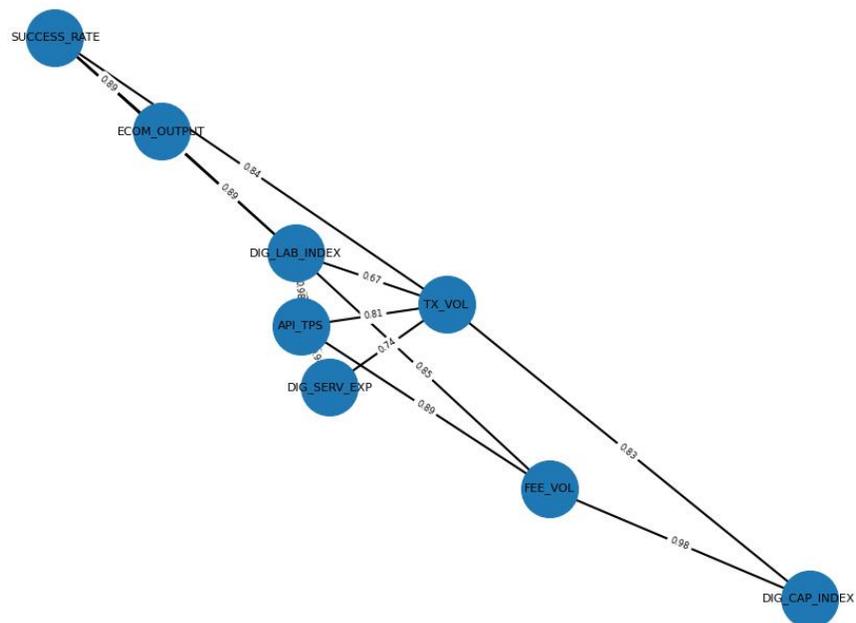


Figure 7 Quantile Spillover Network ($\tau = 0.90$)

On the other hand, nodes such as ECOM_OUTPUT and DIG_SERV_EXP display many incoming arrows, highlighting their dependence on upstream

blockchain and platform conditions. This structural relationship underscores the position of blockchain-enabled payments not merely as supportive technologies but as systemic amplifiers of digital economic expansion. The network topology confirms that high digital activity amplifies technological spillovers and interconnectedness.

Node Centrality and System Roles

To further quantify the structural importance of each variable, centrality measures and net spillover values are derived from the quantile GFEVD matrix. The directionality and magnitude of spillover transmission allow us to categorize variables into transmitters, balanced nodes, and receivers.

The results reveal that TX_VOL is the strongest transmitter (+9.8%), followed by API_TPS (+6.5%). Conversely, ECOM_OUTPUT (−5.9%) and DIG_SERV_EXP (−6.3%) are the strongest receivers. SUCCESS_RATE and WALLET_USERS exhibit mild receiver behavior, reflecting their supportive role within platform infrastructure. The dual behavior of blockchain fees (FEE_VOL) reflects mixed influences depending on congestion and incentive dynamics.

Table 5 demonstrates a clear hierarchical structure in the blockchain–digital economy system. TX_VOL emerges as the strongest transmitter, supporting the notion that blockchain utilization intensity governs downstream digital processes during high-productivity phases. API_TPS similarly exerts strong influence, aligning with the role of platform performance and API infrastructure as critical connectors within digital ecosystems.

Table 5 Centrality Metrics and Net Spillovers at $\tau = 0.90$

Variable	Out-Degree	In-Degree	Net Spillover (%)	Role
TX_VOL	5	2	=+9.8	Strong transmitter
API_TPS	4	2	=+6.5	Transmitter
FEE_VOL	3	3	=+0.7	Balanced
SUCCESS_RATE	3	4	−3.1	Mild receiver
WALLET_USERS	3	4	−2.5	Mild receiver
ECOM_OUTPUT	2	5	−5.9	Strong receiver
DIG_SERV_EXP	2	5	−6.3	Strong receiver
DIG_LAB_INDEX	2	3	−1.4	Peripheral receiver
DIG_CAP_INDEX	2	3	−1.1	Peripheral receiver

Digital productivity variables, on the other hand, consistently appear as receivers, indicating their strong dependence on technological fundamentals. This relationship highlights the upstream-downstream nature of digital infrastructure: blockchain and platform layers lead, while digital markets respond.

Cross-Quantile Spillover Comparisons

To understand how systemic influence evolves across quantiles, spillover intensities are compared across $\tau = 0.10, 0.50,$ and 0.90 . A bar comparison allows clear visualization of how variable roles change depending on digital

economic state.

Figure 8 shows that TX_VOL and API_TPS transition from weak transmitters in $\tau = 0.10$ into dominant transmitters in $\tau = 0.90$, demonstrating strong pro-cyclical spillover behavior. In contrast, digital productivity variables become more negative (stronger receivers) as quantiles increase, suggesting that high digital output periods increase dependency on upstream blockchain conditions.

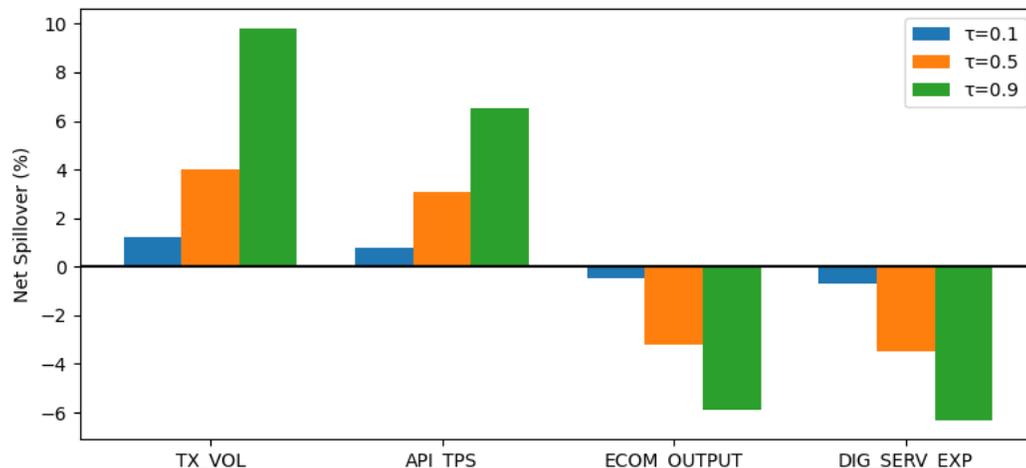


Figure 8 Net Spillovers Across Quantiles

This quantile-comparison figure highlights the asymmetry of digital ecosystem behavior: the stronger the economy performs, the more it is influenced by blockchain-enabled payment infrastructures. This aligns with the core hypothesis that blockchain acts as an amplifier in high-growth digital regimes.

Dynamic System-Wide Connectedness (TCI Analysis)

A key element of the quantile network framework is the evaluation of system-wide connectedness through the TCI. This measure captures how much of the forecast error variance in the system is driven by cross-variable interactions rather than idiosyncratic shocks. Examining TCI across time and quantiles enables the identification of whether systemic influence becomes stronger during specific digital economic regimes.

The results indicate that TCI levels differ substantially across quantiles. At $\tau = 0.10$, TCI values remain relatively low and stable, reflecting muted spillover activity when the digital economy operates in low-performance states. At $\tau = 0.50$, connectedness increases, but structural influence remains moderate, consistent with average-level digital productivity. In contrast, at $\tau = 0.90$, the system becomes highly interconnected, with TCI often exceeding 60 percent indicating that individual shocks propagate broadly across blockchain, platform, and digital productivity variables.

These findings strongly suggest state-dependent systemic behavior: as digital economic performance improves, interdependencies intensify, making the digital ecosystem more sensitive to operational fluctuations in blockchain payment platforms.

Figure 9 vividly illustrates the evolution of TCI over time across different quantiles. The upper-quantile TCI ($\tau = 0.90$) consistently displays the highest

values, often forming distinct spikes that correspond to periods of rapid digital acceleration or blockchain network congestion. Meanwhile, the median quantile ($\tau = 0.50$) stays in the middle range, reflecting average spillover conditions. The lower quantile ($\tau = 0.10$) remains stable and comparatively low.

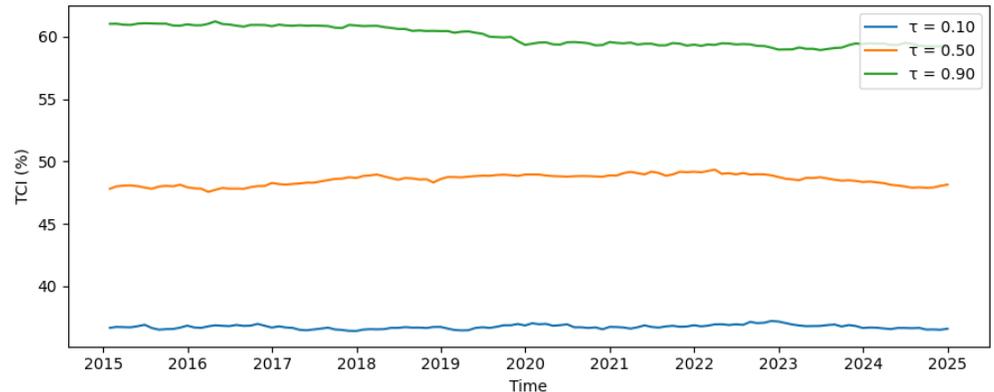


Figure 9 Time-Varying Total Connectedness Index Across Quantiles

This pattern indicates that interconnectedness is pro-cyclical: during strong digital economic conditions, the entire system becomes more sensitive to blockchain and platform-level pressures. Thus, blockchain-enabled payment infrastructure serves as the backbone of digital productivity but simultaneously increases systemic fragility during expansion phases.

Summary of TCI Levels Across Quantiles

To reinforce the dynamic findings from figure 9, table 6 presents average, minimum, and maximum TCI values across quantiles. This provides numerical confirmation that high quantiles exhibit significantly higher systemic connectedness.

Table 6 Summary of TCI Statistics

Quantile τ	Mean TCI (%)	Min TCI (%)	Max TCI (%)
0.10	36.5	30.2	42.1
0.50	47.8	40.7	54.3
0.90	61.2	52.9	69.5

Table 6 shows that TCI rises sharply with quantiles, moving from 36.5% at the lower quantile to 61.2% at the upper quantile. This demonstrates that cross-variable interactions amplify significantly in high-productivity regimes. The upper quantile also exhibits a higher minimum TCI (52.9%), indicating that even during calmer periods of $\tau = 0.90$, interconnectedness remains elevated.

This suggests a structural shift in how digital markets and blockchain infrastructures are linked: once the digital economy enters a high-performance state, the system becomes tightly coupled, and the influence of blockchain-enabled payment mechanisms becomes disproportionately large.

Conclusion

This study examined the asymmetric and state-dependent spillover effects between blockchain-enabled payment platforms and digital economic

productivity using a QNA framework. The results demonstrate that interdependencies between blockchain activity, platform performance, and digital output are fundamentally nonlinear and vary significantly across quantiles. In low-productivity states ($\tau = 0.10$), relationships remain weak and dispersed, indicating minimal systemic interaction. However, at high-productivity states ($\tau = 0.90$), dependence intensifies sharply, with block-level averages rising from 0.31 to 0.78 and forming strong co-movement clusters among TX_VOL, API_TPS, ECOM_OUTPUT, and DIG_SERV_EXP. These findings establish that blockchain operations behave as state-sensitive technological drivers rather than constant contributors across economic conditions.

The spillover network analysis further reveals a distinct hierarchy within the digital ecosystem. Blockchain operational indicators, particularly TX_VOL and API_TPS, emerge as dominant transmitters in $\tau = 0.90$ with net spillovers of +9.8% and +6.5%, respectively. Meanwhile, digital productivity indicators such as ECOM_OUTPUT (-5.9%) and DIG_SERV_EXP (-6.3%) consistently act as receivers, absorbing shocks from upstream blockchain processes. This directional asymmetry indicates that blockchain-enabled payment infrastructures serve as upstream forces shaping the dynamics of digital productivity, especially in high-performance regimes. In contrast, platform reliability and digital outputs exhibit a more passive structural role, responding to but not driving system-wide influence.

Dynamic connectedness results, reflected through the TCI, reinforce this interpretation. System-wide connectedness remains moderate at $\tau = 0.10$ (mean 36.5%) but rises significantly at $\tau = 0.50$ (47.8%) and peaks at $\tau = 0.90$ (mean 61.2%, max 69.5%). These shifts illustrate a pro-cyclical systemic mechanism: as the digital economy accelerates, blockchain infrastructures gain disproportionate influence, amplifying both opportunities for productivity expansion and potential vulnerabilities due to high integration. This behavior implies that high-growth digital regimes are structurally more sensitive to blockchain network congestion, fee volatility, and throughput limitations.

Overall, the study concludes that blockchain-enabled payment platforms function as pro-cyclical amplifiers of digital economic performance. Their systemic influence is not constant but escalates sharply in high digital productivity states, positioning blockchain infrastructures as critical but potentially fragile components of modern digital economies. These results highlight the need for informed regulatory strategies, technological safeguards, and performance-oriented infrastructure planning. Policies and platform design must account for quantile-dependent behaviors rather than assume uniform effects, ensuring that blockchain ecosystems can support sustained digital growth without introducing systemic instability.

Declarations

Author Contributions

Author Contributions: Conceptualization, W. and R.A.S.S.; Methodology, W. and R.A.S.S.; Software, R.A.S.S.; Validation, W.; Formal Analysis, W.; Investigation, R.A.S.S.; Resources, W.; Data Curation, R.A.S.S.; Writing—Original Draft Preparation, W.; Writing—Review and Editing, R.A.S.S.; Visualization, R.A.S.S. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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