

Article

Structural Determinants of NFT and DeFi Adoption: Cross-National Evidence on Technological Readiness, Income Heterogeneity, and Regulatory Clarity

Jampal Dolma ^{1,*}, Annop Thananchana ¹ and Tirapot Chandarasupsang ²¹ International College of Digital Innovation, Chiang Mai University, Chiang Mai 50200, Thailand; annop.t@cmu.ac.th² Independent Researcher, Chiang Mai 50200, Thailand; tirapot@gmail.com

* Correspondence: jampaldolma@gmail.com

Abstract

Regulatory permissiveness is widely prescribed as the primary institutional lever for digital asset adoption. This study challenges that prescription. Analyzing NFT and DeFi adoption across 105 countries using Principal Component Analysis (PCA)-constructed composite indices and multivariate Ordinary Least Squares (OLS) regression, we find that the Frontier Technology Readiness Index (FTRI) is the dominant structural correlate across all specifications, consistently outperforming competing explanatory variables. Regulatory environments neither independently explain adoption nor are associated with it linearly: both permissive and restrictive environments outperform mostly prohibited jurisdictions, suggesting that regulatory clarity rather than permissiveness is the operative institutional dimension. NFT and DeFi markets follow empirically distinct pathways: NFT adoption shows stronger associations with digital marketplace maturity while DeFi is more closely associated with technological infrastructure, suggesting that treating Web3 as a homogeneous policy category is unwarranted. National income conditions how effectively technological readiness is associated with adoption gains, with structural determinants exhibiting considerably reduced explanatory power in lower-middle-income economies. For policymakers, these findings reframe the debate: the primary structural correlate of digital asset adoption is technological capacity, not regulatory stance, and below a development threshold, neither intervention is reliably associated with adoption gains.

Keywords: NFT adoption; DeFi adoption; Frontier Technology Readiness Index; cross-country analysis; crypto regulation; Web3 diffusion; income heterogeneity; regulatory clarity; blockchain adoption

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1. Introduction

Non-Fungible Tokens (NFT) and Decentralized Finance (DeFi) markets have expanded rapidly over the past decade, yet adoption remains concentrated in a small number of technologically advanced economies. Uneven adoption risks deepening existing inequalities, concentrating the financial and economic benefits of blockchain innovation in already advanced economies while leaving developing countries further behind ([Abdulahakeem & Hu, 2021](#); [Jaumotte et al., 2007](#); [OECD, 2024](#)). This uneven pattern raises a fundamental question: is cross-national variation in NFT and DeFi adoption shaped by underlying

structural conditions, or primarily by speculative and market-driven dynamics that defy systematic explanation? This study argues that structural conditions play a more decisive role than speculative dynamics in explaining cross-national variation in NFT and DeFi adoption, with technological capacity emerging as the dominant structural correlate rather than regulatory stance.

Among the most prominent innovations of blockchain technology, NFTs and DeFi represent distinct yet increasingly interconnected applications. NFTs enable the verifiable ownership and exchange of digital assets including art, music, gaming, and media through smart contracts (Dowling, 2022b), creating new monetization opportunities that allow creators to bypass traditional intermediaries (Hemenway Falk et al., 2022; Razi et al., 2024; Wilson et al., 2022). DeFi reconfigures traditional financial services such as lending, borrowing, and trading by replacing centralized intermediaries with smart contract-based protocols (Adwani & Rao, 2025; Schär, 2021), leveraging blockchain transparency to support efficiency and broaden financial access (Alamsyah et al., 2024; Chen & Bellavitis, 2019; Harvey et al., 2021). Both technologies operate on the same underlying blockchain infrastructure, meaning that structural conditions enabling one are likely to enable the other. Their increasing functional convergence, including NFT-collateralized DeFi lending, tokenized ownership structures, and overlapping user bases (Binance, 2023; Kim et al., 2022; KPMG, 2022; Qadir & Naumov, 2022), further suggests that adoption determinants may operate similarly across both domains. At the same time, treating them as analytically distinct allows this study to test whether structural determinants operate with different intensities across the two technologies, an empirical question that has not been systematically examined at the cross-national level (Alshater et al., 2025; Gramlich et al., 2023). This joint yet differentiated approach is a distinctive feature of the present study.

Existing research has advanced the understanding of crypto and blockchain adoption, but important gaps remain. Studies have largely focused on micro-level dynamics such as investor sentiment, price volatility, and market behavior, or on single-country case studies that limit generalizability (Dowling, 2022b; Makarov & Schoar, 2022; Schär, 2021). Where macro-level analyses exist, they typically examine aggregate cryptocurrency adoption rather than NFTs and DeFi as distinct technologies (Gramlich et al., 2023), obscuring potentially important structural differences between the two. The structural conditions shaping NFT and DeFi adoption remain underexplored across countries, and whether regulatory clarity rather than permissiveness is the operative institutional dimension has not been empirically tested across a large and diverse sample.

This study provides one of the first systematic cross-national empirical analyses of NFT and DeFi adoption across 105 countries, integrating economic, technological, and institutional determinants within a unified framework and explicitly modeling income-based heterogeneity and regulatory interaction effects. Three interrelated research questions operationalize this inquiry: which structural determinants most strongly explain cross-country adoption (RQ1); how national income level conditions the influence of the Frontier Technology Readiness Index, digital commerce, and crypto regulatory environments on NFT and DeFi adoption (RQ2); and whether crypto regulatory environments moderate the effects of FTRI and digital commerce on adoption (RQ3).

From a financial risk management perspective, these questions carry direct institutional relevance. Regulatory uncertainty constitutes a primary source of jurisdiction-level risk in digital asset markets (Auer & Claessens, 2018), while technological capacity constraints shape whether financial innovation is associated with sustainable market development (UNCTAD, 2023a). Understanding which structural conditions are associated with adoption, and under what institutional configurations, informs how regulators, financial

institutions, and development authorities assess and manage the risks associated with Web3 market entry and expansion.

The remainder of the paper is organized as follows: Section 2 reviews the literature and establishes the research gap; Section 3 presents the theoretical framework; Section 4 details the methodology; Section 5 reports empirical results; Section 6 presents robustness checks; and Sections 7–10 discuss findings, limitations, policy implications, and conclusions.

2. Literature Review

This literature review examines structural determinants of NFT and DeFi adoption across three domains: economic conditions, technological readiness, and institutional environments. Each domain is reviewed in terms of its theoretical relevance and expected relationship with adoption outcomes, building toward the integrated empirical framework developed in Section 3.

2.1. Economic Conditions

2.1.1. GDP Growth

Economic growth reflects the macroeconomic opportunity environment in which experimentation with emerging digital assets is more likely to occur. During periods of expansion, NFT markets experienced substantial growth and DeFi platforms attracted capital through yield farming and speculative trading (Dowling, 2022a; Makarov & Schoar, 2022). Economic downturns reveal asymmetric effects, with DeFi demonstrating relative resilience while NFT demand contracts (James et al., 2024; Ugolini et al., 2023). At the aggregate level, GDP growth is therefore expected to exert a weak and inconsistent effect on adoption, functioning as a background condition rather than a structural driver.

2.1.2. Gini Index (Income Inequality)

The Gini index captures socioeconomic dispersion relevant to digital asset participation. Adoption exhibits strong concentration among high-income actors, with approximately 85% of NFT transactions conducted by the top 10% of users (Nadini et al., 2021), and DeFi usage skewing toward financially sophisticated participants (OECD, 2022, 2024). Yet blockchain-based technologies are simultaneously promoted as tools for financial inclusion (Abdulhakeem & Hu, 2021; Wilson et al., 2022), suggesting that income inequality may exert offsetting effects depending on whether enabling infrastructure exists to convert latent demand into actual participation.

2.1.3. Income Heterogeneity and Development Level

Beyond aggregate economic conditions, national income level may condition the effectiveness of structural determinants of adoption rather than simply explaining adoption levels directly. Participation in digital asset markets skews heavily toward higher-income economies with greater institutional capacity, financial depth, and market sophistication (OECD, 2022, 2024). In lower-income contexts, structural barriers including limited technological infrastructure, weak financial systems, and underdeveloped institutional environments may attenuate the returns to technological investment and regulatory reform (UNCTAD, 2023a, 2023b), suggesting that the same structural mechanisms may operate with fundamentally different intensity across development contexts. This conditioning role of income is distinct from its direct effect on adoption levels and remains underexplored in existing cross-national digital asset research, representing a gap this study addresses.

2.2. Technological Readiness

2.2.1. Global Crypto Adoption Index

The Global Crypto Adoption Index captures the extent to which digital assets are embedded within national economies, reflecting peer-to-peer usage, remittance activity, and grassroots adoption ([Bitstamp, n.d.](#); [Chainalysis, 2024](#)). However, grassroots crypto exposure does not automatically translate into NFT or DeFi participation, as low adoption constrains ecosystem development through weak infrastructure and limited trust ([Metelski & Sobieraj, 2022](#)). Broad crypto adoption thus represents a necessary though not sufficient condition for decentralized financial innovation and is treated as a proximate rather than structural correlate in this study, with its explanatory power expected to diminish once deeper technological readiness is controlled for.

2.2.2. Internet Penetration

Reliable and widespread internet access constitutes a foundational prerequisite for NFT and DeFi adoption, as blockchain-based systems require consistent connectivity for transaction validation, smart contract execution, and platform interaction ([Ante & Fiedler, 2025](#); [Bin Hasan et al., 2024](#)). However, internet penetration is expected to function as a threshold condition rather than a structural driver, consistent with the TOE framework's distinction between foundational connectivity and substantive technological capacity, with its marginal effect diminishing once broader technological readiness is accounted for.

2.2.3. Frontier Technology Readiness Index (FTRI)

The Frontier Technology Readiness Index (FTRI) provides a comprehensive measure of a country's capacity to adopt and diffuse emerging technologies across five dimensions: ICT infrastructure, skills development, research and development, industrial capacity, and access to finance ([UNCTAD, 2023a, 2023b](#)). High FTRI countries possess robust innovation ecosystems characterized by sustained R&D investment, advanced digital infrastructure, and strong institutional support ([Jordan Strategy Forum, 2022](#); [UNCTAD, 2023b](#)). In contrast, countries with low FTRI face structural barriers including limited technological infrastructure and gaps in technical education, which constrain the scalability of decentralized platforms ([UNCTAD, 2023b](#)). Unlike single-dimension indicators, FTRI captures higher-order technological capabilities that shape whether digital asset ecosystems can transition from early experimentation to sustained adoption. Among all technological readiness indicators, FTRI is expected to emerge as the dominant structural correlate given its comprehensive multidimensional coverage.

2.2.4. Digital Commerce

The expansion of digital commerce has increased consumer familiarity with online transactions, digital payments, and virtual ownership, potentially facilitating early adoption of NFTs and DeFi ([Albshaier et al., 2024](#); [Taherdoost & Madanchian, 2023](#)). Platforms such as Shopify illustrate the convergence between traditional e-commerce and decentralized technologies by enabling NFT sales and cryptocurrency payments ([Shopify, n.d.-a, n.d.-b](#)), and strong digital commerce infrastructure combined with fintech integration has been shown to support blockchain adoption, as seen in South Korea ([Weisman-Pitts, 2025](#)). Nevertheless, digital commerce alone is insufficient in the absence of broader technological readiness, suggesting a complementary rather than dominant role.

2.3. Institutional Environment

Crypto Regulatory Environments

Crypto regulatory environments are commonly classified into four categories: Mostly Legal Investment, Explicit Ban, Implicit Ban, and Significant Concerns or Restrictions (Corva, 2023). Countries with clear legal frameworks, such as the United States, Germany, and Singapore, provide investor protection and regulatory certainty (Kaulartz & Noller, 2023; MAS, 2023; Tarbert et al., 2019). By contrast, Explicit Bans such as those implemented in China are associated with more limited NFT and DeFi development, constraining access to global liquidity and innovation networks (Houben & Snyers, 2018; People's Bank of China, 2021), while Implicit Bans and environments characterized by Significant Concerns or Restrictions, such as those observed in Kuwait and India, generate uncertainty that discourages institutional participation (Central Bank of Kuwait, 2021; Mehrotra, 2024). Recent financial economics research suggests that regulatory clarity rather than permissiveness is associated with reduced institutional uncertainty and greater market participation (Auer & Claessens, 2018; Zetzsche et al., 2020). Critically, this classification suggests that what matters for adoption may be whether a defined regulatory stance exists at all, rather than whether that stance is permissive, a distinction this study empirically examines. Regulatory environments are therefore expected to operate conditionally rather than independently, with clarity rather than permissiveness as the operative institutional dimension.

2.4. Convergence of NFTs and DeFi

NFTs and DeFi exhibit increasing functional convergence, with DeFi protocols enabling NFT-based lending, borrowing, and yield generation (Binance, 2023; Kim et al., 2022), and NFTs introducing novel asset classes into DeFi ecosystems through fractionalization and tokenized ownership structures (KPMG, 2022; Qadir & Naumov, 2022). Empirical evidence suggests substantial overlap in user participation driven by shared motivations related to decentralization and digital ownership (Herrera, 2021; Loon & Harwood, 2021). This convergence suggests that a unified analytical framework capturing both technologies is not only appropriate but necessary for understanding the structural conditions shaping Web3 adoption at the macro level, while maintaining their empirical distinction.

2.5. Research Gap

Despite growing scholarly attention to NFTs and DeFi, existing research largely examines these technologies in isolation or within narrowly defined national contexts (Alshater et al., 2025; Dowling, 2022a; Makarov & Schoar, 2022; Wilson et al., 2022). Prior studies emphasize behavioral, speculative, or market-level dynamics, offering limited insight into the structural correlates of adoption at scale. The structural conditions underlying cross-country variation in NFT and DeFi adoption remain poorly understood, and whether the two technologies follow different structural diffusion pathways has not been systematically examined across a large cross-national sample.

Beyond the absence of prior cross-national work, existing NFT and DeFi studies have also failed to explain several theoretical questions that this study addresses directly. Studies examining market behavior and technology mechanisms have not tested whether structural determinants operate with different intensities across development contexts. Studies examining regulatory environments have assumed permissiveness is the operative institutional dimension without empirically testing whether clarity rather than permissiveness is what conditions adoption. Studies that consider income have treated it as a direct predictor rather than as a moderator of structural mechanisms. And studies that examine cryptocurrency adoption at the macro level have not maintained the analytical distinction between NFTs and DeFi necessary to test whether their structural diffusion pathways differ.

IDT (Rogers, 2003) and TOE (Tornatzky & Fleischer, 1990) frameworks were originally developed in organizational contexts and have not been systematically extended to address these questions at the cross-national level.

These theoretical limitations motivate the integrated framework developed in Section 3. This study addresses both dimensions by providing one of the first systematic cross-national empirical analyses of NFT and DeFi adoption across 105 countries, extending IDT, TOE, and Institutional Theory to a macro-level context while explicitly modelling income-based heterogeneity and regulatory interaction effects.

3. Theoretical Framework

This study integrates Innovation Diffusion Theory (IDT) (Rogers, 2003), the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), and Institutional Theory (North, 1990) to explain cross-national variation in NFT and DeFi adoption. Together, these perspectives provide a multi-level framework in which economic conditions, technological readiness, and institutional environments jointly shape the diffusion of blockchain-based innovations. The Frontier Technology Readiness Index (FTRI) is conceptualized as the primary structural correlate, with economic and institutional determinants operating conditionally through it. Critically, institutional environments are expected to matter not through permissiveness but through clarity, consistent with the study's central empirical argument.

3.1. Innovation Diffusion Theory (IDT): Economic Exposure and Awareness

IDT posits that adoption depends on perceived relative advantage, compatibility, observability, and trialability (Rogers, 2003). Applied at the national level, it captures how economic conditions and prior crypto exposure shape awareness and normalization of blockchain technologies. GDP growth reflects the macroeconomic opportunity environment in which experimentation with emerging digital assets is more likely to occur (Fairchild et al., 2022), while the Gini index captures how structural inequality may concentrate participation among affluent users, limiting broad-based uptake (Nadini et al., 2021; OECD, 2022). The Global Crypto Adoption Index proxies observability and social exposure, where high existing cryptocurrency usage reduces informational barriers and may accelerate diffusion through behavioral spillovers (Gramlich et al., 2023; Metelski & Sobieraj, 2022). IDT variables are expected to exert secondary rather than dominant effects. In the empirical model, IDT is operationalized through GDP growth, the Gini index, and the Global Crypto Adoption Index.

3.2. Technology-Organization-Environment (TOE) Framework: Technological Readiness as the Primary Structural Determinant

The TOE framework emphasizes that adoption depends on technological infrastructure, organizational capabilities, and environmental conditions (Tornatzky & Fleischer, 1990). Internet penetration captures the foundational connectivity threshold required for blockchain participation (Ante & Fiedler, 2025; Ozili, 2022), though its marginal effect is expected to diminish once broader technological readiness is accounted for. Digital commerce reflects the maturity of a country's digital transaction ecosystem, including consumer trust, payment interoperability, and familiarity with digital ownership (Albshaier et al., 2024; Taherdoost & Madanchian, 2023). It is expected to be particularly relevant for NFT adoption given its reliance on consumer-facing digital infrastructure, while DeFi adoption is expected to depend more strongly on deep technological capacity and access to finance. The FTRI serves as the primary structural determinant, capturing ICT deployment, skills development, R&D intensity, industrial capacity, and access to finance (UNCTAD, 2023a, 2023b). Countries with high technological readiness are better positioned to integrate

decentralized technologies into broader economic activity, while low-readiness environments face structural barriers regardless of demand conditions or regulatory stance. In the empirical model, TOE is operationalized through internet penetration, digital commerce, and FTRI.

3.3. Institutional Theory: Legitimacy and Conditional Regulatory Effects

Institutional Theory emphasizes how formal regulations, informal norms, and cognitive expectations shape the legitimacy of innovation (North, 1990). Crypto regulatory environments are associated with reduced uncertainty and greater institutional participation (Kaulartz & Noller, 2023; MAS, 2023; Tarbert et al., 2019), but their effects are conceptualized as primarily conditional rather than independent. Crucially, what matters is not whether regulation is permissive but whether a clearly defined regulatory stance exists at all. Both permissive and restrictive environments are expected to outperform mostly prohibited jurisdictions, as defined regulatory frameworks create operating conditions within which technological readiness is associated with adoption, regardless of whether that stance is liberal or cautious (Houben & Snyers, 2018; People's Bank of China, 2021). This conditionality motivates the interaction specifications in RQ2 and RQ3. Income inequality also carries institutional implications, as financial exclusion may increase the appeal of decentralized alternatives (Abdulhakeem & Hu, 2021; Wilson et al., 2022), but without enabling infrastructure, this latent demand is unlikely to materialize at scale. In the empirical model, Institutional Theory is operationalized through the crypto regulatory environment indicators and the collapsed Regulatory Index used in interaction specifications.

3.4. Integrated Framework and Empirical Implications

Integrating IDT, TOE, and Institutional Theory yields a framework where economic conditions shape awareness and exposure, technological readiness operates as the primary structural determinant, and institutional environments condition how effectively that readiness is associated with adoption gains. Economic variables are expected to exert weaker and inconsistent effects. Crypto regulatory environments are expected to operate conditionally rather than independently, with clarity rather than permissiveness as the operative institutional dimension. FTRI is expected to emerge as the dominant structural correlate across development contexts, with its effects attenuating progressively in lower-income economies where complementary institutional and financial conditions are weaker. These theoretical expectations are consistent with financial market development literature, which emphasizes that institutional capacity and technological infrastructure are preconditions for the emergence of new asset classes and financial instruments (Levine, 2005). While IDT, TOE, and Institutional Theory were originally developed in organizational contexts, this study applies them at the national level, treating countries as the unit of analysis and macro-level structural variables as proxies for the mechanisms each theory identifies. This adaptation extends these frameworks beyond their original scope to explain cross-national variation in emerging technology adoption.

4. Materials and Methods

4.1. Research Design

The analytical framework draws on IDT, the TOE framework, and Institutional Theory to assess how economic conditions, technological readiness, and institutional environments jointly shape adoption outcomes. A cross-sectional approach is adopted due to asymmetric data availability across key explanatory variables, particularly Gini index (income inequality) and crypto regulatory measures, which are available for a single year in most countries. In contrast, variables such as internet penetration, digital commerce, the FTRI,

GDP growth, and the Global Crypto Adoption Index are consistently available for the most recent year, allowing reliable cross-country comparison. While this cross-sectional approach precludes causal inference and limits the ability to capture adoption dynamics over time, it is appropriate given current data constraints and consistent with existing cross-national studies of emerging technology adoption. The empirical analysis proceeds in three stages. First, composite indices capturing NFT Composite Index, DeFi Composite Index, and Combined Adoption Index are constructed using Principal Component Analysis (PCA). Second, multivariate OLS regressions are estimated to evaluate baseline structural determinants (RQ1). Third, interaction and heterogeneity models are estimated to examine income-group moderation (RQ2) and crypto regulatory interaction effects (RQ3). To account for heteroskedasticity across national contexts, all models are estimated using HC3 robust standard errors.

4.2. Research Questions

The study addresses three interrelated research questions:

RQ1: Baseline Structural Determinants: Which economic, technological, and institutional determinants most strongly explain cross-country NFT and DeFi adoption, and what is their relative importance?

RQ2: Heterogeneous Effects Across Income Groups: How does national income level condition the influence of the Frontier Technology Readiness Index, digital commerce, and crypto regulatory environments on NFT and DeFi adoption?

RQ3: Crypto Regulatory Interaction Effects: Do crypto regulatory environments moderate the effects of FTRI and digital commerce on cross-country NFT and DeFi adoption?

4.3. Dependent Variable Construction

Three adoption indices are constructed to capture distinct dimensions of digital asset uptake (Table 1):

Table 1. Composition of Adoption Indices.

Index	Components
NFT Composite Index	NFT revenue; NFT user penetration
DeFi Composite Index	DeFi revenue; DeFi user penetration
Combined Adoption Index	All four indicators

Revenue and user penetration data are sourced from Statista’s Digital Assets market outlook, which provides annual cross-sectional estimates for 2023 across 100+ countries (Statista, n.d.-a, n.d.-c). Statista constructs these estimates using a bottom-up methodology that combines verified transaction data from blockchain analytics providers, nationally representative consumer surveys, and proprietary market intelligence models calibrated to regional digital payment infrastructure. Country-level estimates reflect the most recent available year and are updated annually. While commercial data sources carry inherent limitations, including potential inconsistencies in country-level estimation methodologies, no publicly available alternative provides comparable coverage across 105 countries for these specific market segments. The adoption indices are constructed as composite measures using PCA precisely to reduce dependence on any single metric and to minimize measurement noise, partially mitigating concerns about individual variable reliability. Findings should be interpreted with this data limitation in mind, and future research should validate these results as more granular public data becomes available.

All component variables are first standardized using z-scores to ensure comparability across scales. PCA is then applied separately to construct the NFT, DeFi, and combined

adoption indices. For each index, only the first principal component is retained, based on the Kaiser criterion (eigenvalue > 1) and inspection of scree plots. PCA is preferred over equal weighting to allow data-driven aggregation and reduce measurement noise among correlated indicators. For the NFT and DeFi Composite indices, revenue and user penetration load symmetrically (0.707), explaining 57.9% and 63.7% of total variance respectively. The Combined Adoption Index exhibits differentiated loadings across indicators: NFT revenue (0.569) and DeFi revenue (0.565) contribute most strongly, followed by DeFi user penetration (0.456) and NFT user penetration (0.387), explaining 58.2% of total variance. The differentiated loading structure of the Combined Index reflects the distinct market characteristics of NFT and DeFi components while still satisfying the Kaiser criterion for single-factor extraction, justifying retention of the first principal component as the composite measure.

4.4. Independent Variables and Conceptual Grouping

4.4.1. Economic Conditions

GDP growth captures macroeconomic dynamism, while the Gini index proxies income inequality and socioeconomic dispersion.

4.4.2. Technological Readiness

Internet penetration, digital commerce, the Global Crypto Adoption Index, and the FTRI capture digital infrastructure, market maturity, and readiness to adopt advanced technologies. FTRI reflects broader innovation capacity, encompassing ICT deployment, skills development, R&D intensity, industrial capacity, and access to finance.

4.4.3. Institutional Environment

Crypto regulatory environments are operationalized using mutually exclusive binary indicators. The reference category, Explicit Ban (used interchangeably with ‘mostly prohibited’ throughout this study), reflects the most restrictive crypto regulatory stance. The remaining categories, Implicit Ban, Significant Concerns or Restrictions, and Mostly Legal Investment, each indicate a progressively more permissive crypto regulatory environment, with each country assigned to exactly one category. For interaction and robustness analyses (RQ2 and RQ3), crypto regulatory categories are additionally collapsed into an ordinal Regulatory Index, where higher values indicate more permissive crypto regulatory environments. This collapsed index reduces the number of categories while preserving their relative ordering. Regulatory Index takes a value of 1 for Mostly Legal Investment, −1 for Significant Concerns or Restrictions, and Implicit Bans, and 0 for neutral or unclassified contexts. Implicit Ban and Significant Concerns or Restrictions are assigned the same value of −1 because both represent environments where crypto activity faces meaningful institutional barriers without formal prohibition, making their operational distinction less consequential than their shared departure from regulatory clarity. This coding choice reflects a deliberate theoretical rationale rather than an arbitrary decision. The theoretically consequential distinction is between environments that provide regulatory clarity and those that do not, regardless of whether that lack of clarity takes the form of an implicit ban or significant concerns. As a concrete illustration from the data, Bahrain (Implicit Ban) prohibits banks from dealing in crypto assets while Angola (Significant Concerns or Restrictions) has yet to introduce any regulatory framework for cryptocurrencies (Corva, 2023). Both create institutional uncertainty without formal prohibition, meaning their shared departure from regulatory clarity is more consequential than the operational distinction between them. The theoretical equivalence between these two categories is not merely conceptual but can be examined directly through the disaggregated robustness check in Table A8, where the FTRI × Implicit Ban interaction (NFT: coef = 0.469, $p = 0.088$; Combined: coef = 0.331,

$p = 0.056$) and the FTRI $\times$ Significant Concerns or Restrictions interaction (NFT: coef = 0.545, $p < 0.001$; Combined: coef = 0.390, $p = 0.002$) are both positive and of comparable magnitude relative to the Explicit Ban baseline. While the Implicit Ban interactions approach rather than reach conventional significance thresholds, the directional consistency and comparable magnitude across both categories strengthens rather than undermines the theoretical equivalence argument. The ordinal scaling preserves the directional ordering of regulatory stances while reducing dimensionality for interaction specifications.

Table 2 summarizes the operationalization, measurement, and data sources for all variables used in the analysis.

Table 2. Variable Operationalization and Data Sources.

Variable	Domain	Description	Source
GDP growth	Economic Conditions	Annual percentage change in GDP. Cross-sectional values reflect the most recent available year.	(World Bank Group, n.d.-a)
Gini index	Economic Conditions	Income inequality measured on a 0–100 scale; 0 = perfect equality. Cross-sectional values reflect the most recent available year.	(World Bank Group, n.d.-b)
Digital commerce	Technological Readiness	Total value of online consumer transactions (USD millions), reflecting the scale and maturity of digital market activity.	(Statista, n.d.-b)
Internet penetration	Technological Readiness	Percentage of the national population with internet access. Cross-sectional values reflect the most recent available year.	(World Bank Group, n.d.-c)
Global Crypto Adoption Index	Technological Readiness	Quantifies cryptocurrency adoption within each country on a 0–1 scale for 2023.	(Chainalysis, 2023)
FTRI	Technological Readiness	Measures national readiness to adopt frontier technologies across five dimensions: ICT infrastructure, skills development, R&D intensity, industrial capacity, and access to finance.	(UNCTAD, 2023b)
Crypto Regulatory Environments	Institutional Environment	Classifies national regulatory stance into four mutually exclusive categories: Mostly Legal Investment, Significant Concerns or Restrictions, Implicit Ban, and Explicit Ban (reference).	(Corva, 2023)
Internet penetration 2015 †	Robustness Check	Percentage of national population with internet access in 2015. Used as instrumental variable for FTRI in 2SLS endogeneity check only.	(World Bank Group, n.d.-c)
FTRI Components (ICT, Skills, R&D, Industry, Finance) †	Robustness Check	Five constituent sub-indices of the composite FTRI score used in component decomposition analysis only.	(UNCTAD, n.d.)

Notes: † Variables marked with † are used exclusively in robustness checks reported in Appendix A and are not included in baseline OLS specifications. † Internet penetration 2015 was obtained from the same World Bank indicator as current internet penetration, filtered to the 2015 data year.

4.5. Model Specification

Separate OLS regressions were estimated for each adoption index (NFT, DeFi, Combined):

$$\text{Adoption}_{it} = \beta_0 + \beta_1(\text{GDP growth}) + \beta_2(\text{Gini index}) + \beta_3(\text{Internet penetration}) + \beta_4(\text{Global Crypto Adoption Index}) + \beta_5(\text{Significant Concerns or Restrictions}) + \beta_6(\text{Mostly Legal Investment}) + \beta_7(\text{Implicit Ban}) + \beta_8(\text{Digital commerce}) + \beta_9(\text{FTRI}) + \varepsilon_{it}, \quad (1)$$

where:

Adoption_{it} denotes the NFT Composite Index, DeFi Composite Index, or Combined Adoption Index for country i , β_0 is the intercept, and ε_{it} is the error term. HC3-robust standard errors were applied throughout. The reference crypto regulatory category is Explicit Ban.

4.6. Interaction and Heterogeneity Analysis

To address RQ2, interaction models were estimated between World Bank income-group indicators (low, lower-middle, upper-middle, and high income) and three key explanatory variables: FTRI, digital commerce, and the collapsed Regulatory Index. High-income economies serve as the reference category as they represent the development context in which the structural framework is most likely to hold, allowing interaction terms to capture how effects attenuate at lower development levels. Income-group main effects capture baseline adoption level differences across development stages, while interaction terms isolate slope heterogeneity, specifically whether the association between each structural variable and adoption differs across income groups. To address RQ3, two-way interaction terms were estimated between the Regulatory Index and both FTRI and digital commerce as the primary specification. All continuous variables entering interaction terms were mean-centered to reduce multicollinearity and aid interpretation. Marginal effects were computed for all interaction models. The low-income group comprises only five observations in the sample and interaction estimates for this group carry very large standard errors and are not interpreted substantively.

4.7. Robustness and Sensitivity Checks

Econometric diagnostics include heteroskedasticity testing using the Breusch-Pagan test, influence diagnostics using Cook's Distance, and multicollinearity assessment using Variance Inflation Factors (VIFs) and mean VIF across all model specifications. HC3-robust standard errors were used throughout. For RQ1, baseline models were re-estimated using log-transformed dependent variables to assess sensitivity to functional form. Additionally, Two-Stage Least Squares (2SLS) estimation was conducted using internet penetration in 2015 as an instrument for FTRI to address potential endogeneity between technological readiness and adoption outcomes. Quantile regression was also estimated at the 25th, 50th, and 75th percentiles of the adoption distribution to assess whether FTRI's dominance holds across low, medium, and high adoption countries rather than only at the mean. For RQ2, split-sample estimation by income group was conducted to verify the stability of heterogeneous effects across development levels. For RQ3, the collapsed Regulatory Index was replaced with separate binary crypto regulatory category indicators to examine whether the moderation pattern differs across specific crypto regulatory environments. A three-way interaction specification involving FTRI, crypto regulatory environments, and digital commerce was also estimated as an exploratory extension to assess whether regulatory context amplifies or attenuates the relationship between technological readiness and adoption. Further, digital commerce was log-transformed as a robustness check to assess whether the elevated VIF values observed in the main RQ3 specification affect

the stability of key findings. Finally, the composite FTRI was decomposed into its five constituent dimensions, specifically ICT infrastructure, skills development, R&D intensity, industrial capacity, and access to finance, and re-estimated in the baseline specification to identify which sub-component most strongly predicts adoption. Detailed results are presented in Section 6 and Appendix A.

4.8. Data Treatment and Sample

The final sample consists of 105 countries with complete observations across all variables. Missing data are addressed using listwise deletion. Missingness was minimal and did not materially affect sample composition or comparability across specifications. The sample covers 49 high-income, 26 upper-middle-income, 25 lower-middle-income, and 5 low-income economies, providing broad geographic and developmental coverage. All analyses are conducted in Python (version 3.12.13). Pandas was used for data management, Statsmodels for OLS regression estimation, and Scikit-learn for Principal Component Analysis.

5. Results

5.1. RQ1: Which Economic, Technological, and Institutional Determinants Most Strongly Explain Cross-Country NFT and DeFi Adoption, and What Is Their Relative Importance?

To identify the economic, technological, and institutional determinants of cross-country NFT and DeFi adoption, baseline OLS regressions were estimated for the NFT Composite Index, DeFi Composite Index, and Combined Adoption Index using HC3-robust standard errors. The models explain substantial variation in adoption outcomes ($R^2 = 0.708\text{--}0.851$) and are jointly significant at the 1% level (F-statistics $p < 0.001$). Full coefficient estimates, robust standard errors, and p -values are reported in Table 3.

Table 3. Baseline OLS Regression Results: Determinants of NFT, DeFi, and Combined Adoption (RQ1).

Variable	NFT Composite Index	DeFi Composite Index	Combined Adoption Index
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Constant	−0.1256 ** (0.059) [0.034]	−0.0513 (0.037) [0.162]	−0.0884 ** (0.042) [0.036]
Sig. Concerns/Restrictions	0.0481 (0.050) [0.334]	0.0038 (0.029) [0.894]	0.0260 (0.036) [0.465]
Implicit Ban	0.0190 (0.052) [0.713]	−0.0081 (0.031) [0.795]	0.0054 (0.038) [0.885]
Mostly Legal Investment	0.0514 (0.049) [0.293]	−0.0115 (0.029) [0.695]	0.0200 (0.035) [0.566]
Digital commerce	0.0002 (0.000) [0.109]	0.0003 (0.000) [0.323]	0.0002 (0.000) [0.235]
Global Crypto Adoption Index	−0.0096 (0.066) [0.884]	0.0656 (0.067) [0.331]	0.0280 (0.047) [0.554]
Internet penetration	1.960×10^{-5} (0.001) [0.974]	0.0006 (0.001) [0.256]	0.0003 (0.000) [0.474]
FTRI	0.3878 *** (0.063) [<0.001]	0.3956 *** (0.068) [<0.001]	0.3917 *** (0.053) [<0.001]
Gini index	0.0011 (0.001) [0.155]	0.0006 (0.001) [0.261]	0.0008 † (0.000) [0.059]
GDP growth	0.0021 (0.002) [0.389]	-1.480×10^{-5} (0.001) [0.992]	0.0010 (0.002) [0.548]
Model Fit Statistics			
R^2	0.708	0.851	0.851
Adj. R^2	0.680	0.837	0.837
F-statistic	23.88	64.02	59.15
Prob (F-statistic)	<0.001	<0.001	<0.001
Observations	105	105	105

Notes: OLS estimates with HC3-robust standard errors in parentheses; p -values in brackets. *** $p < 0.01$, ** $p < 0.05$, † $p < 0.10$. Reference crypto regulatory category: Explicit Ban. $N = 105$ countries. All models jointly significant at the 1% level. A Breusch-Pagan test fails to reject homoskedasticity ($LM = 4.40$, $p = 0.883$), confirming HC3 as a conservative specification choice. Mean VIF = 2.93, indicating no serious multicollinearity across regressors.

5.1.1. Technological Readiness

FTRI is the strongest predictor of adoption across all specifications ($p < 0.001$), outperforming economic and institutional determinants across all three adoption indices.

A one-unit increase in FTRI is associated with a 0.39–0.40 increase in adoption, indicating that countries with greater technological readiness exhibit markedly higher levels of Web3 participation. Coefficients are 0.388 for NFT and 0.396 for DeFi, confirming that both technologies are associated with the same technological foundation to a similar degree. Where they begin to diverge is in their secondary drivers, particularly in the role of digital commerce.

Digital commerce is positively associated with NFT and DeFi adoption across all models but does not reach statistical significance in either specification. However, the p -value for NFT Composite Index ($p = 0.109$) sits closer to conventional thresholds than for DeFi Composite Index ($p = 0.323$), suggesting a directional pattern consistent with NFT markets carrying greater sensitivity to digital marketplace maturity. This directional difference is consistent with the consumer-facing nature of NFT ecosystems relative to DeFi's more infrastructural character.

By contrast, internet penetration exhibits no statistically significant marginal effect once FTRI is accounted for, suggesting that basic connectivity is a necessary but insufficient condition for early-stage Web3 adoption. What matters is the broader technological ecosystem rather than foundational infrastructure alone.

The Global Crypto Adoption Index shows no statistically significant association with NFT or DeFi adoption in baseline regressions. The index captures aggregate cryptocurrency activity rather than NFT- or DeFi-specific engagement, meaning broad crypto exposure alone does not explain domestic Web3 adoption once structural technological readiness is controlled for.

5.1.2. Institutional Environment

Crypto regulatory environments, whether characterized by Significant Concerns or Restrictions, Implicit Bans, or Mostly Legal Investment frameworks, do not exhibit statistically significant effects in any baseline specification. This null result suggests that crypto regulatory environments alone do not explain adoption at this stage, with conditional regulatory effects examined in RQ3.

5.1.3. Economic Conditions

Traditional macroeconomic indicators, including GDP growth and the Gini index, are not statistically significant predictors of NFT or DeFi adoption across specifications. The Gini index approaches marginal significance for Combined Adoption Index ($p = 0.059$) but does not reach conventional thresholds in the NFT or DeFi specifications individually. Given this inconsistency across outcome measures, it is not interpreted as a robust finding.

5.1.4. Differential Adoption Patterns

The explanatory power of the models is notably higher for DeFi Composite Index ($R^2 = 0.851$) than for NFT Composite Index ($R^2 = 0.708$). The consistently high R^2 values across specifications are attributable to FTRI's multidimensional structure, which simultaneously captures ICT deployment, skills development, R&D activity, industry capacity, and access to finance. As a composite index spanning multiple structural dimensions, FTRI naturally accounts for a large share of cross-national variation in technology adoption outcomes. This does not indicate variable overlap with the dependent variable, as FTRI measures readiness capacity while the adoption indices measure actual market outcomes.

DeFi adoption follows more uniform structural patterns, closely associated with technological readiness. NFT adoption is more fragmented, with platform-specific and consumer demand dynamics playing a role that aggregate structural variables do not fully capture at the cross-national level. This also explains why the Combined Adoption Index

closely mirrors DeFi dynamics. NFT and DeFi markets are complementary but associated with different underlying conditions, a distinction developed further in the discussion.

5.2. RQ2: How Does National Income Level Condition the Influence of the Frontier Technology Readiness Index, Digital Commerce, and Crypto Regulatory Environments on NFT and DeFi Adoption?

To assess whether structural determinants of adoption operate differently across development levels, interaction models were estimated in which FTRI, digital commerce, and crypto regulatory environments are interacted with World Bank income groups. The low-income group is retained for completeness but comprises only five observations and is therefore not interpreted substantively. The interaction models explain substantial variation in adoption outcomes ($R^2 = 0.750$ for NFT, 0.878 for DeFi, and 0.882 for Combined Adoption) and are jointly significant at the 1% level. Full coefficient estimates and marginal effects are reported in Tables 4 and 5.

Table 4. Determinants of NFT, DeFi, and Combined Adoption: Income-Group Interaction Models (RQ2).

Variable	NFT Composite Index	DeFi Composite Index	Combined Adoption Index
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Frontier Technology Readiness Index (FTRI)			
FTRI	0.4910 *** (0.107) [<0.001]	0.3667 *** (0.098) [<0.001]	0.4288 *** (0.079) [<0.001]
×Upper-Middle	−0.2229 (0.229) [0.330]	−0.0618 (0.157) [0.694]	−0.1423 (0.140) [0.310]
×Lower-Middle	−0.3636 (0.236) [0.123]	−0.2408 (0.152) [0.114]	−0.3022 † (0.154) [0.050]
×Low †	−0.7986 (8.151) [0.922]	−0.0507 (0.491) [0.918]	−0.4246 (4.307) [0.921]
Digital commerce			
Digital commerce	0.0002 *** (0.000) [<0.001]	0.0003 (0.000) [0.307]	0.0002 † (0.000) [0.086]
×Upper-Middle	0.0011 (0.001) [0.287]	0.0010 (0.001) [0.203]	0.0010 (0.001) [0.228]
×Lower-Middle	0.0009 (0.005) [0.851]	−0.0003 (0.003) [0.917]	0.0003 (0.001) [0.805]
×Low †	0.0687 (1.222) [0.955]	0.3788 *** (0.091) [<0.001]	0.2238 (0.646) [0.729]
Crypto regulatory environments			
Regulatory Index	−0.0232 (0.018) [0.209]	−0.0104 (0.018) [0.554]	−0.0168 (0.014) [0.215]
×Upper-Middle	0.0456 † (0.025) [0.065]	−0.0003 (0.022) [0.990]	0.0227 (0.017) [0.192]
×Lower-Middle	0.0592 (0.039) [0.125]	0.0307 (0.028) [0.275]	0.0449 † (0.025) [0.070]
×Low †	−0.0827 (3.299) [0.980]	−0.8277 *** (0.237) [<0.001]	−0.4552 (1.744) [0.794]
Baseline Controls			
GDP growth	0.0015 (0.002) [0.508]	−0.0005 (0.002) [0.771]	0.0005 (0.002) [0.745]
Gini index	0.0011 (0.001) [0.187]	0.0003 (0.001) [0.649]	0.0007 (0.001) [0.215]
Global Crypto Adoption Index	−0.0261 (0.174) [0.881]	0.1578 (0.099) [0.111]	0.0658 (0.101) [0.513]
Internet penetration	−0.0001 (0.001) [0.909]	0.0011 (0.001) [0.190]	0.0005 (0.001) [0.522]
Model Fit Statistics			
R^2	0.750	0.878	0.882
Adj. R^2	0.695	0.851	0.856
F-statistic	52.43	151.3	78.63
Prob (F-statistic)	<0.001	<0.001	<0.001
Observations	105	105	105

Notes: OLS estimates with HC3-robust standard errors in parentheses; p -values in brackets. *** $p < 0.01$, † $p < 0.10$. Reference category: High-income economies. Reference crypto regulatory category: Explicit Ban. All variables are mean-centered. † Low-income group comprises $N = 5$ observations; all low-income estimates carry very large standard errors and should not be interpreted substantively. Mean VIF for main regressors = 2.10, indicating no serious multicollinearity. The elevated condition number (4.39×10^5) reflects expected collinearity among higher-order interaction terms without compromising the reliability of main coefficient estimates. Income-group main effects included but not shown, available on request.

The estimated model is:

$$\text{Adoption}_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 \text{Income Group}_i + \beta_3 (X_{it} \times \text{Income Group}_i) + \gamma Z_{it} + \varepsilon_{it}, \quad (2)$$

where X_{it} represents FTIRI, digital commerce, or crypto regulatory environments, and Z_{it} denotes the controls: GDP growth, Gini index, and the Global Crypto Adoption Index. Income-group coefficients capture baseline differences in adoption levels, while interaction terms isolate slope heterogeneity conditional on those baseline differences.

Table 5. Marginal Effects of Key Variables by Income Group (RQ2).

Variable	Income Group	NFT Composite Index	DeFi Composite Index	Combined Adoption Index
		Coef. [95% CI]	Coef. [95% CI]	Coef. [95% CI]
FTIRI	High	0.4910 [0.2821, 0.6998]	0.3667 [0.1753, 0.5581]	0.4288 [0.2749, 0.5827]
	Upper-Middle	0.2681 [−0.1171, 0.6533]	0.3049 [0.0578, 0.5520]	0.2865 [0.0582, 0.5148]
	Lower-Middle	0.1273 [−0.3593, 0.6139]	0.1259 [−0.1644, 0.4163]	0.1266 [−0.1841, 0.4373]
	Low ‡	−0.3077 [−16.2800, 15.6700]	0.3160 [−0.6340, 1.2660]	0.0042 [−8.4370, 8.4460]
Digital commerce	High	2.000×10^{-4} [1.00×10^{-4} , 3.00×10^{-4}]	3.000×10^{-4} [-2.00×10^{-4} , 8.00×10^{-4}]	2.000×10^{-4} [−0.00, 5.00×10^{-4}]
	Upper-Middle	0.0013 [− 7.00×10^{-4} , 0.0032]	0.0013 [− 2.00×10^{-4} , 0.0028]	0.0013 [− 4.00×10^{-4} , 0.0029]
	Lower-Middle	0.0011 [−0.0085, 0.0107]	−0.000 [−0.0050, 0.0050]	6.000×10^{-4} [−0.0020, 0.0032]
	Low ‡	0.0689 [−2.3260, 2.4630]	0.3791 [0.1997, 0.5585]	0.2240 [−1.0420, 1.4900]
Regulatory Index	High	−0.0232 [−0.0594, 0.0130]	−0.0104 [−0.0450, 0.0241]	−0.0168 [−0.0434, 0.0098]
	Upper-Middle	0.0224 [−0.0083, 0.0531]	−0.0107 [−0.0370, 0.0156]	0.0059 [−0.0161, 0.0278]
	Lower-Middle	0.0360 [−0.0305, 0.1025]	0.0203 [−0.0242, 0.0648]	0.0281 [−0.0138, 0.0700]
	Low ‡	−0.1059 [−6.5720, 6.3600]	−0.8381 [−1.3030, −0.3740]	−0.4720 [−3.8900, 2.9460]

Notes: Marginal effects derived from the pooled interaction models in Table 4, calculated as the sum of the main effect and the relevant interaction term for each income group. 95% confidence intervals in brackets based on HC3-robust standard errors. ‡ Low-income group (N = 5): confidence intervals are extremely wide, and estimates are not reliable.

5.2.1. Frontier Technology Readiness Index (FTIRI)

FTIRI is positive and statistically significant in high-income economies across all three adoption indices ($p < 0.001$). Marginal effects reveal a clear attenuation gradient across income groups. For NFT adoption, the marginal effect falls from 0.491 in high-income economies to 0.268 in upper-middle-income and 0.127 in lower-middle-income economies. A similar gradient is observed for DeFi and Combined Adoption indices. Interaction terms are negative throughout but do not reach conventional significance except for the Combined Adoption Index at the lower-middle-income level ($p = 0.050$), which should be interpreted cautiously. For DeFi specifically, FTIRI remains significant in both high-income ($p < 0.001$) and upper-middle-income economies ($p = 0.012$ in split-sample estimation) but loses significance in lower-middle-income contexts ($p = 0.371$), indicating attenuation but not reversal. The structural framework loses explanatory power more considerably in lower-middle-income economies, where models are jointly insignificant for NFT and combined adoption ($F p = 0.711$ and $p = 0.137$ respectively), suggesting that below a certain development threshold the variables that perform well in higher-income contexts offer limited explanatory power in lower-middle-income settings.

5.2.2. Digital Commerce

Digital commerce shows a positive and significant marginal effect on NFT adoption in high-income economies in the pooled interaction model (coef = 0.0002, $p < 0.001$), consistent with NFT markets' sensitivity to consumer-facing digital infrastructure. However, this result is not replicated in split-sample estimation ($p = 0.627$), indicating sensitivity to model specification. Effects across upper-middle- and lower-middle income groups are small and insignificant throughout. A large significant coefficient appears for the low-income group

in the DeFi model (coef = 0.379, $p < 0.001$) but is driven by the five-observation subsample and does not replicate in split-sample estimation.

5.2.3. Crypto Regulatory Environments

Crypto regulatory environments show no statistically significant associations with adoption across any income group or specification. Marginal effects are consistently small and imprecisely estimated, and null results persist in split-sample estimation. The apparent negative coefficient for the low-income group in the DeFi model is driven by the five-observation subsample and is not interpretable. Baseline controls including GDP growth, Gini index, internet penetration, and the Global Crypto Adoption Index show no robust associations across income groups or specifications.

5.3. RQ3: Do Crypto Regulatory Environments Moderate the Effects of FTRI and Digital Commerce on Cross-Country NFT and DeFi Adoption?

To examine whether crypto regulatory environments condition the influence of FTRI and digital commerce on adoption, two-way interaction models were estimated incorporating terms between a collapsed regulatory index and each key explanatory variable. The Regulatory Index takes a value of 1 for permissive environments (Mostly Legal Investment), -1 for restrictive environments (Significant Concerns or Restrictions and Implicit Bans), and 0 for neutral or unclassified contexts.

Two specifications are estimated. The first uses a collapsed Regulatory Index that treats regulation as a continuous scale from restrictive to permissive. The second replaces this with separate binary indicators for each regulatory category. The reason for both is straightforward. If the moderation effect is non-linear, meaning both permissive and restrictive environments behave differently from prohibited ones (Explicit Ban) rather than differently from each other, the collapsed Regulatory Index will miss it while the disaggregated specification will not. All models are estimated using OLS with HC3-robust standard errors. Results for the collapsed Regulatory Index are reported in Table 6 and disaggregated results in Table 7.

Table 6. Regulatory Moderation of FTRI and Digital commerce: Two-Way Interaction Models: Collapsed Regulatory Index (RQ3).

Variable	NFT Composite Index	DeFi Composite Index	Combined Adoption Index
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Main Effects			
FTRI	0.3683 *** (0.040) [<0.001]	0.4277 *** (0.040) [<0.001]	0.3980 *** (0.033) [<0.001]
Regulatory Index	-0.0049 (0.017) [0.767]	-0.0124 (0.016) [0.425]	-0.0087 (0.015) [0.556]
Digital commerce	0.0004 (0.000) [0.266]	0.0004 (0.000) [0.268]	0.0004 (0.000) [0.253]
Two-Way Interaction Terms			
FTRI $\times$ Regulatory Index	0.0389 (0.043) [0.361]	-0.0203 (0.043) [0.634]	0.0093 (0.037) [0.801]
Digital commerce $\times$ Regulatory Index ‡	-0.0003 (0.000) [0.569]	-0.0002 (0.000) [0.733]	-0.0002 (0.000) [0.639]
Model Fit Statistics			
R ²	0.694	0.847	0.845
Adj. R ²	0.678	0.840	0.838
F-statistic	56.01	114.2	111.8
Prob (F-statistic)	<0.001	<0.001	<0.001
Observations	105	105	105

Notes: OLS estimates with HC3-robust standard errors in parentheses; p -values in brackets. *** $p < 0.01$. All variables are mean-centered. Regulatory Index = 1 (mostly legal investment), -1 (significant concerns or restrictions, and implicit ban), 0 (neutral/unclassified). ‡ Digital commerce interaction term exhibits high multicollinearity (VIF ≈ 18.3 – 18.6); interpret with caution. FTRI interaction estimates are unaffected (VIF < 2). Mean VIF = 8.38, see Table A10 for full VIF diagnostics.

Table 7. Regulatory Moderation of FTRI and Digital commerce: Disaggregated Regulatory Category Models (RQ3).

Variable	NFT Composite Index	DeFi Composite Index	Combined Adoption Index
	Coef. (SE) [<i>p</i>]	Coef. (SE) [<i>p</i>]	Coef. (SE) [<i>p</i>]
Main Effects			
FTRI	−0.187 (0.126) [0.137]	0.247 ** (0.090) [0.006]	0.030 (0.097) [0.757]
Digital commerce	0.003 (0.020) [0.884]	0.008 (0.010) [0.465]	0.005 (0.015) [0.729]
Mostly Legal Investment	−0.153 (0.100) [0.125]	−0.029 (0.047) [0.540]	−0.091 (0.068) [0.182]
Implicit Ban	−0.093 (0.133) [0.487]	−0.017 (0.057) [0.758]	−0.055 (0.088) [0.534]
Sig. Concerns or Restrictions	−0.134 (0.093) [0.151]	−0.047 (0.046) [0.309]	−0.090 (0.067) [0.178]
FTRI Interaction Terms			
FTRI × Mostly Legal Investment	0.585 *** (0.139) [<0.001]	0.158 (0.098) [0.106]	0.372 *** (0.104) [<0.001]
FTRI × Implicit Ban	0.469 † (0.275) [0.088]	0.192 (0.153) [0.211]	0.331 † (0.173) [0.056]
FTRI × Sig. Concerns or Restrictions	0.545 *** (0.150) [<0.001]	0.236 † (0.123) [0.055]	0.390 ** (0.124) [0.002]
Digital commerce Interaction Terms			
DC × Mostly Legal Investment	−0.003 (0.020) [0.863]	−0.005 (0.010) [0.611]	−0.004 (0.015) [0.773]
DC × Implicit Ban	−0.010 (0.026) [0.718]	−0.010 (0.013) [0.413]	−0.010 (0.016) [0.533]
DC × Sig. Concerns or Restrictions	−0.003 (0.020) [0.889]	−0.006 (0.010) [0.579]	−0.004 (0.015) [0.778]
Model Fit Statistics			
R ²	0.730	0.864	0.862
Adj. R ²	0.694	0.846	0.844
F-statistic	31.57	57.48	47.09
Prob (F-statistic)	<0.001	<0.001	<0.001
Observations	105	105	105

Notes: OLS estimates with HC3-robust standard errors in parentheses; *p*-values in brackets. *** $p < 0.01$, ** $p < 0.05$, † $p < 0.10$. Reference crypto regulatory category: Explicit Ban. All variables are uncentred. Condition number = 2.23×10^4 ; elevated due to collinearity among regulatory interaction terms. DC = Digital commerce; interaction estimates for DC should be interpreted cautiously. The FTRI main effect in this model represents its association within the mostly prohibited reference category only and should not be interpreted as an overall effect.

5.3.1. Baseline Effects

FTRI remains positive and statistically significant across all three specifications ($p < 0.001$). The Regulatory Index shows no significant direct association with adoption in any model, and digital commerce does not show a robust independent effect once FTRI is accounted for.

5.3.2. Collapsed Regulatory Index: Interaction Effects

Two-way interaction terms between the Regulatory Index and both FTRI and digital commerce are small and statistically insignificant across all specifications. The FTRI × Regulatory Index interaction does not reach significance for NFT ($p = 0.361$), DeFi ($p = 0.634$), or Combined Adoption ($p = 0.801$), indicating that FTRI effects do not vary systematically across permissive and restrictive environments when regulation is treated as a single ordered dimension. Digital commerce interactions are similarly insignificant across all specifications.

One technical qualification applies. The digital commerce variable and its interaction term exhibit high Variance Inflation Factors (VIF = 18.6 and 18.3 respectively), reducing the precision of those specific estimates. FTRI interaction coefficients are unaffected (VIF = 1.26–1.89).

5.3.3. Disaggregated Crypto Regulatory Categories

When the collapsed Regulatory Index is replaced with separate binary indicators for each crypto regulatory environment, the results differ considerably. Note that in this specification the FTRI main effect represents its association within the mostly prohibited

(Explicit Ban) reference category only and should not be interpreted as an overall effect. For NFT and Combined Adoption, FTRI interactions with both the Mostly Legal Investment category (NFT: coef = 0.585, $p < 0.001$; Combined: coef = 0.372, $p < 0.001$) and the Significant Concerns or Restrictions category (NFT: coef = 0.545, $p < 0.001$; Combined: coef = 0.390, $p = 0.002$) are positive and statistically significant. This indicates that FTRI effects are stronger in both permissive and restrictive crypto regulatory environments relative to the mostly prohibited baseline, suggesting that the moderation pattern may be non-linear and that the collapsed index was potentially masking this heterogeneity.

For DeFi adoption, disaggregated interactions are weaker. The FTRI $\times$ Mostly Legal Investment term is positive but not significant ($p = 0.106$), and FTRI $\times$ Significant Concerns or Restrictions approaches significance ($p = 0.055$). The FTRI $\times$ Implicit Ban interaction does not reach conventional thresholds, though marginal effects approach significance for NFT ($p = 0.088$) and Combined Adoption ($p = 0.056$).

Digital commerce interactions with crypto regulatory environments are insignificant across all specifications. One exception is a negative and significant FTRI $\times$ digital commerce interaction for DeFi ($p = 0.037$) in the disaggregated model, but this does not replicate in the collapsed Regulatory index or three-way interaction specifications and should be treated cautiously given the elevated condition number (2.23×10^4).

6. Robustness and Sensitivity Analysis

Robustness checks address functional form sensitivity, influential observations, multicollinearity, endogeneity, distributional assumptions, and result stability across alternative specifications, sample partitions, and variable decompositions. Full results are reported in Appendix A.

6.1. Robustness of Baseline Determinants (RQ1)

6.1.1. Heteroskedasticity and Functional Form

All baseline regressions use HC3 robust standard errors throughout. A Breusch-Pagan test fails to reject homoskedasticity (LM = 4.40, $p = 0.883$), confirming HC3 as a conservative rather than corrective specification choice. Baseline models were re-estimated using log-transformed dependent variables (Table A1). FTRI remains positive and statistically significant across all three adoption measures, confirming that FTRI's dominant association with adoption holds under log transformation. Internet penetration and the Global Crypto Adoption Index retain their expected directional associations under log transformation in the combined adoption model.

6.1.2. Influential Observations

Cook's Distance identifies between seven and nine influential observations depending on the outcome variable. Re-estimating after excluding these observations does not materially alter coefficient signs, magnitudes, or significance (Table A2). FTRI remains stable throughout, indicating baseline results are not driven by a small number of extreme cases.

6.1.3. Multicollinearity

VIF diagnostics confirm no serious multicollinearity among baseline regressors, with all values below VIF = 6 and mean VIF = 2.93 (Table A3). The elevated condition number (2.06×10^3) is attributable to the intercept and does not affect substantive regressors.

6.1.4. Endogeneity

To address the potential endogeneity between FTRI and digital asset adoption, the baseline RQ1 models were re-estimated using Two-Stage Least Squares (2SLS) estimation. Internet penetration in 2015 was employed as an instrument for FTRI on the grounds

that historical connectivity infrastructure predicts current technological readiness but does not directly predict 2023 adoption outcomes through channels other than technological readiness. The instrument predates NFT and DeFi markets by five or more years, as these technologies only emerged at scale after 2020. The instrument is strong, with a partial F-statistic of 42.12 ($p < 0.001$), well above the conventional threshold of 10 (Staiger & Stock, 1997). Full results are reported in Table A13. FTRI remains positive and statistically significant across all three outcome measures under 2SLS estimation (NFT: $\beta = 0.389$, $p = 0.026$; DeFi: $\beta = 0.515$, $p < 0.001$; Combined: $\beta = 0.452$, $p < 0.001$), indicating that its dominant association with adoption is not an artifact of reverse causality. The FTRI coefficient is larger under 2SLS for DeFi and Combined Adoption than under OLS (OLS: 0.396 and 0.392 respectively; 2SLS: 0.515 and 0.452), implying that OLS may underestimate the true structural effect of technological readiness. Additionally, digital commerce reaches statistical significance across all three specifications under 2SLS ($p < 0.001$), suggesting its effect was partially suppressed by multicollinearity with FTRI in the OLS specification.

6.1.5. Distributional Robustness

To assess whether FTRI's dominance holds across the full adoption distribution rather than only at the mean, quantile regression was estimated at the 25th, 50th, and 75th percentiles for all three outcome measures (Table A14). FTRI is positive and statistically significant at $p < 0.001$ across all quantiles and all three outcome measures, with coefficients ranging from 0.384 to 0.449, confirming that its dominant association with adoption holds across the full distribution rather than being driven by outliers or mean-specific effects. Of particular note, FTRI coefficients at Q25 are comparable to or larger than those at Q75 for NFT and Combined Adoption, indicating that technological readiness is at least as consequential for low-adoption countries as for high-adoption ones. Digital commerce also reaches statistical significance across most quantiles and outcomes, consistent with the 2SLS results.

6.1.6. FTRI Component Decomposition

To identify which constituent dimension of FTRI most strongly predicts adoption, the composite index was disaggregated into its five sub-components namely, ICT infrastructure, skills development, R&D intensity, industrial capacity, and access to finance, using component scores from UNCTAD (n.d.) and re-estimated in the baseline RQ1 specification (Table A15). Two components emerge as dominant. Skills development is positive and statistically significant across all three outcome measures (NFT: $\beta = 0.222$, $p = 0.003$; DeFi: $\beta = 0.168$, $p = 0.001$; Combined: $\beta = 0.195$, $p < 0.001$). R&D intensity is similarly significant (NFT: $\beta = 0.166$, $p = 0.039$; DeFi: $\beta = 0.265$, $p < 0.001$; Combined: $\beta = 0.216$, $p < 0.001$), with a notably larger coefficient for DeFi, consistent with the argument that DeFi protocols require deeper research capacity than consumer-facing NFT markets. ICT infrastructure, industrial capacity, and access to finance do not reach statistical significance, suggesting that basic connectivity and financial access alone are not sufficient to explain cross-national variation in NFT and DeFi adoption.

6.2. Robustness of Heterogeneous Effects Across Income Groups (RQ2)

6.2.1. Split-Sample Stability Across Income Groups

Full split-sample results are reported in Table A4 (NFT), Table A5 (DeFi), and Table A6 (Combined Adoption). FTRI remains positive and statistically significant in high-income economies across all three outcome measures (NFT: $p = 0.001$; DeFi: $p = 0.014$; Combined: $p < 0.001$) and retains significance for DeFi and Combined Adoption in upper-middle-income economies ($p = 0.012$ and $p = 0.037$ respectively). The income-conditioned primacy of FTRI is therefore not sensitive to model choice or sample partitioning.

In lower-middle-income economies, FTRI coefficients are positive but insignificant across all outcome measures. Split-sample models are jointly insignificant for NFT ($F p = 0.711$) and combined adoption ($F p = 0.137$), reinforcing that the structural framework explains limited variation in these economies.

6.2.2. Multicollinearity

Digital commerce and crypto regulatory coefficients are not stable across income groups or specifications. Significance appears only in the low-income interaction terms for DeFi, attributable to the five-observation subsample and not estimable in split-sample analysis. Maximum VIF for main regressors is 4.56 for FTRI, reported in Table A7. The elevated condition number (4.39×10^5) reflects expected collinearity among higher-order interaction terms without compromising the reliability of main coefficient estimates.

6.3. Robustness of Crypto Regulatory Interaction Results (RQ3)

6.3.1. Three-Way Interaction Test

Full results are reported in Table A9. A three-way interaction specification between FTRI, the Regulatory Index, and digital commerce yields insignificant three-way interaction terms across all outcome measures (NFT: $p = 0.899$; DeFi: $p = 0.245$; Combined: $p = 0.790$), confirming no joint higher-order moderation effects. One exception is a negative FTRI $\times$ digital commerce two-way interaction in the DeFi model (coef = -0.004 , $p = 0.044$), but this does not replicate under the collapsed two-way specification or the disaggregated model and is not treated as a robust finding.

6.3.2. Disaggregated Regulatory Categories and Multicollinearity

The disaggregated crypto regulatory category model produces significant FTRI $\times$ crypto regulatory category interactions for NFT and Combined Adoption, but these effects are not replicated consistently across DeFi specifications and are sensitive to the choice of regulatory proxy. The elevated condition number (2.23×10^4) reflects collinearity among regulatory dummy interactions and warrants caution in interpreting individual coefficients, though the joint significance of the FTRI interactions suggests the pattern is unlikely to be purely a statistical artifact.

VIF values for FTRI and its interaction term are acceptable ($VIF < 2$). Digital commerce and its interaction with the Regulatory Index exhibit high VIF values (approximately 18.6 and 18.3 respectively; see Table A8 for full disaggregated model results and Table A10 for VIF diagnostics), reducing the precision of those specific estimates without affecting FTRI-related coefficients. Across all specifications, FTRI remains positive and statistically significant and its interaction with the collapsed regulatory index remains insignificant.

6.3.3. Log-Transformed Digital Commerce

As an additional robustness check, digital commerce was log-transformed to address the elevated VIF values observed in the main specification. Log transformation reduced VIF for digital commerce and its interaction term from approximately 18.6 and 18.3 to 1.95 and 1.83 respectively, suggesting that the original multicollinearity was attributable to the distributional properties of the raw variable rather than fundamental model misspecification. Critically, FTRI $\times$ Regulatory Index interaction terms remain statistically insignificant across all three outcome measures under log transformation (NFT: $p = 0.714$; DeFi: $p = 0.406$; Combined: $p = 0.856$), confirming that the null moderation result is not an artifact of multicollinearity. Full model results are reported in Table A11, and VIF diagnostics for the log-transformed specification are reported in Table A12. The log-transformed specification additionally reveals a significant positive association between digital commerce and adoption across all outcome measures, consistent with its theorized complementary role.

However, the log-transformed specification yields lower explanatory power across all outcome measures and introduces non-normality in the DeFi residuals, supporting the original specification as the preferred model while confirming the robustness of key findings.

7. Discussion

This section interprets the empirical findings in relation to prior research and the three theoretical frameworks guiding the study.

7.1. Shared Technological Foundations, Distinct Market Dependencies (RQ1)

FTRI emerges as the dominant structural correlate of adoption across all specifications, consistently outperforming economic and institutional determinants across all three adoption indices. The results suggest that national-level NFT and DeFi adoption is associated primarily with an economy's capacity to absorb and deploy emerging technologies, rather than its proximity to crypto markets or the permissiveness of its regulatory environment.

Notably, FTRI coefficients are nearly identical across NFT and DeFi specifications (0.388 and 0.396 respectively), indicating that both technologies are associated with the same technological foundation. The differentiation between them emerges elsewhere. Digital commerce, while not reaching conventional significance thresholds in either model, exhibits a meaningfully lower p -value for NFT adoption ($p = 0.109$) than for DeFi ($p = 0.323$). This directional pattern is consistent with the argument that NFT markets carry an additional sensitivity to digital marketplace maturity that DeFi does not, reflecting the more consumer-facing nature of NFT ecosystems relative to DeFi's infrastructural character. This distinction also helps explain the R^2 gap between the two models. DeFi adoption ($R^2 = 0.851$) follows more uniform structural patterns, with a greater share of cross-national variation explained by the structural framework, while NFT adoption ($R^2 = 0.708$) is more fragmented, with marketplace dynamics playing a role. This finding is further supported by quantile regression results suggesting that FTRI's dominant association holds across the full adoption distribution, from low to high adoption countries, rather than being confined to the mean.

Component-level analysis further refines this picture. Disaggregating FTRI into its five constituent dimensions reveals that skills development and R&D intensity are the primary structural correlates of adoption, significant across all three outcome measures. ICT infrastructure, industrial capacity, and access to finance do not reach statistical significance, suggesting that what matters is not basic technological access but the depth of human capital and research investment. The larger R&D coefficient for DeFi relative to NFT is consistent with the argument that DeFi protocols require deeper technological and research capacity than consumer-facing NFT markets.

The insignificance of internet penetration once FTRI is controlled for is consistent with the TOE framework's distinction between threshold conditions and structural determinants. Basic connectivity is necessary but insufficient for advanced blockchain participation. These findings extend the TOE framework beyond its original organizational context, suggesting that technological readiness operates as the primary structural correlate of adoption at the national level, a relationship that existing cross-national digital asset research had not systematically examined.

A similar pattern holds for digital commerce and the Global Crypto Adoption Index, whose insignificance once FTRI is controlled for reflects a conceptually important distinction between structural and proximate correlates of adoption. Digital commerce reflects the maturity of a country's digital transaction ecosystem, which is itself partly a product of broader technological readiness. Once FTRI captures this deeper structural capacity, digital commerce's independent explanatory contribution diminishes. Similarly, the Global

Crypto Adoption Index captures existing cryptocurrency exposure and familiarity, which represents a proximate condition for NFT and DeFi participation rather than a structural determinant. Broad crypto exposure creates awareness and reduces informational barriers, but without the underlying technological infrastructure that FTRI captures, this exposure is not sufficient for sustained NFT or DeFi activity. Both variables therefore function as intermediate rather than foundational correlates, explaining why their independent associations with adoption attenuate once the primary structural determinant is accounted for. This pattern is consistent with the TOE framework's distinction between threshold conditions and structural determinants, where digital commerce and crypto exposure function as enabling conditions that depend on deeper technological capacity rather than operating as independent structural drivers.

7.2. Income Heterogeneity and the Limits of Technological Readiness (RQ2)

The income heterogeneity findings reveal a more complex pattern than a simple relationship between national wealth and digital asset adoption. National income does not merely explain adoption levels; it conditions the effectiveness of the structural mechanisms through which adoption occurs. The extent to which technological readiness is associated with actual NFT and DeFi participation appears to depend on the complementary institutional, financial, and human capital conditions that tend to accompany higher income levels.

The marginal effects in Table 5 capture this attenuation directly. The marginal effect of FTRI on NFT adoption falls from 0.491 in high income economies to 0.268 in upper-middle and 0.127 in lower-middle income economies, with a similar gradient observed for DeFi and Combined Adoption. This is not attributable solely to lower-income countries having lower FTRI scores; the same unit increase in FTRI is associated with progressively weaker adoption gains.

In lower-middle income economies the structural framework loses explanatory power more considerably, with models jointly insignificant for NFT and Combined Adoption. This likely reflects structural constraints already documented in the literature, including limited technological infrastructure and demand patterns oriented toward remittance activity rather than NFT or DeFi engagement (Bitstamp, n.d.; Chainalysis, 2024; UNCTAD, 2023a, 2023b). The low-income subsample comprises only five observations, and findings for this group should not be interpreted substantively. Fully disentangling these mechanisms, however, is beyond what a cross-sectional model can achieve. This has a direct implication for the DeFi financial inclusion narrative: the preconditions for DeFi adoption such as technological infrastructure, institutional depth, and financial system integration are weakest precisely where financial exclusion is most acute (Abdulahakeem & Hu, 2021), suggesting that foundational capacity building may be necessary before Web3-specific interventions can generate meaningful gains.

7.3. Regulatory Clarity over Permissiveness (RQ3)

The baseline expectation was that permissive crypto regulatory environments would enhance the effects of both FTRI and digital commerce on adoption. The results only partially support this. Using the collapsed Regulatory Index, neither FTRI nor digital commerce interactions reach statistical significance, suggesting that when regulation is treated as a simple permissive to restrictive continuum, it does not meaningfully moderate the association between FTRI or digital commerce and adoption.

The more informative pattern emerges from the disaggregated analysis, where treating each regulatory category separately rather than collapsing them into a continuous scale reveals a non-linearity the collapsed Regulatory Index was masking. FTRI effects are

significantly amplified in both permissive and restrictive crypto regulatory environments relative to mostly prohibited jurisdictions for NFT and Combined Adoption. Both permissive and restrictive environments outperform prohibition, suggesting that what matters is whether a defined crypto regulatory framework exists at all. This is consistent with financial economics research suggesting that regulatory clarity rather than permissiveness is associated with reduced institutional uncertainty and greater market participation (Auer & Claessens, 2018; Zetzsche et al., 2020), extending that finding to the specific context of NFT and DeFi adoption across a large cross-national sample. Even restrictive crypto regulation is associated with defined operating conditions within which FTRI correlates with higher adoption, whereas prohibition removes that space entirely regardless of how developed a country's technological capacity is. Given that this pattern holds more robustly for NFT and Combined Adoption than for DeFi, the regulatory clarity finding should be interpreted as suggestive rather than definitive.

Digital commerce moderation is insignificant across all specifications. This is consistent with the argument that digital commerce operates through consumer behavior and market trust rather than institutional frameworks, making it less sensitive to crypto-specific regulation than FTRI (Albshaier et al., 2024; Taherdoost & Madanchian, 2023).

The weaker regulatory moderation pattern for DeFi relative to NFT and Combined Adoption warrants further interpretation. DeFi protocols operate through smart contract infrastructure that is architecturally decentralized and less dependent on nationally bounded regulatory frameworks than NFT marketplace platforms, which rely more heavily on consumer-facing intermediaries subject to domestic oversight. This architectural difference may explain why FTRI moderation by regulatory environment is stronger for NFT and Combined Adoption than for DeFi, where protocol-level participation is less constrained by national institutional conditions. This distinction has direct implications for regulatory design: NFT markets may respond more readily to national regulatory interventions while DeFi ecosystems may require coordinated cross-jurisdictional approaches.

8. Limitations and Future Research

First, the cross-sectional research design was adopted due to data constraints on key institutional and inequality indicators. This approach precludes causal inference and limits the ability to capture how adoption dynamics evolve over time. Future research could exploit panel data as regulatory classifications and inequality measures become available over longer time horizons.

Second, sample size constraints present a related challenge. The low-income group comprises only five observations, meaning interaction estimates for this group carry very large standard errors and cannot be interpreted substantively. Similarly, the Explicit Ban regulatory category comprises only six countries, the majority of which are lower-middle- or low-income economies, raising the possibility that prohibition effects partially reflect development level rather than regulation alone. Both constraints limit the generalizability of findings for these specific subgroups.

Third, crypto regulatory environments are operationalized using categorical indicators that reflect formal legal stances only, rather than enforcement intensity or actual regulatory practice. Future research could incorporate more granular regulatory indices that capture enforcement intensity, compliance costs, and investor protection standards alongside formal classifications, better reflecting the financial regulatory dimensions relevant to institutional participation in digital asset markets.

Fourth, the constructed adoption indices capture revenue and user penetration but do not fully capture qualitative dimensions of ecosystem development such as platform sophistication, protocol interoperability, governance maturity, or the depth of liquidity

and financial intermediation within decentralized ecosystems. Additionally, the adoption indices rely on Statista commercial estimates, which carry inherent measurement uncertainty and may not fully reflect actual blockchain transaction activity at the country level. Future research could integrate ecosystem-level or protocol-level indicators to capture these dimensions more fully.

Fifth, the digital commerce variable and its interaction term exhibit high VIFs in the RQ3 models, reducing the precision of those specific estimates. FTRI interaction coefficients are unaffected by this issue. Future research could explore alternative operationalizations of digital commerce that reduce collinearity with regulatory interaction terms.

Sixth, while FTRI captures multiple dimensions of technological readiness, several potentially relevant institutional and structural determinants are not included in the analysis, such as governance quality, rule of law, financial development, and digital skills measures. The omission of these variables may introduce omitted variable bias, though FTRI's multidimensional structure partially accounts for several of these dimensions by capturing ICT deployment, skills development, R&D activity, industry capacity, and access to finance simultaneously.

Finally, potential endogeneity cannot be fully ruled out. FTRI and digital asset adoption may be jointly determined: while high FTRI is associated with adoption, adoption itself could stimulate further investment in the infrastructure, skills, and innovation capacity that FTRI captures, making the direction of influence difficult to establish with cross-sectional data alone. The 2SLS robustness check reported in Table A13 partially addresses this concern, though it cannot fully resolve the endogeneity challenge given the inherent limitations of cross-sectional instrumental variable estimation.

Targeted regional analyses focusing specifically on low-income and mostly prohibited economies would complement the global cross-country approach taken here and represent a natural extension of the present study.

9. Policy Implications

The findings carry direct implications for financial regulators, innovation agencies, and development authorities engaging with digital asset ecosystems.

- **Prioritize technological infrastructure over standalone regulatory liberalization.**

FTRI is the strongest structural correlate of adoption across all specifications. This association is robust to endogeneity correction, with 2SLS estimation suggesting that FTRI's relationship with adoption is not an artifact of reverse causality. Investments in digital infrastructure, technical skills, and innovation capacity are more strongly associated with adoption gains than regulatory reform alone. In low-readiness environments, regulatory liberalization without accompanying infrastructure development is less likely to generate meaningful adoption gains. Quantile regression results further suggest that the association between technological readiness and adoption is at least as strong for currently low-adoption countries as for high-adoption ones, indicating that infrastructure investment may generate meaningful adoption gains precisely where they are most needed.

- **Target human capital and R&D investment as the most consequential policy levers.**

Component-level decomposition of FTRI reveals that skills development and R&D intensity are the dominant structural correlates of adoption, significant across all three outcome measures. ICT infrastructure, industrial capacity, and access to finance do not reach statistical significance, suggesting that basic connectivity and financial access are necessary but not sufficient conditions. Notably, R&D intensity carries a larger coefficient for DeFi than for NFT adoption, suggesting that countries prioritizing DeFi ecosystem development may benefit from particularly strong investment in research capacity, consistent

with DeFi's greater reliance on technically sophisticated protocol infrastructure relative to the more consumer-facing nature of NFT markets. What matters most is investment in technical education, workforce skills, and research ecosystems rather than broadband rollout or financial system development alone.

- **Adopt context-sensitive regulatory strategies calibrated to development level.**

What matters for policy is not whether regulation is permissive but whether a clear stance exists at all. Both permissive and restrictive environments outperform mostly prohibited jurisdictions, suggesting that establishing a defined regulatory framework, even a cautious one, strengthens how effectively technological readiness is associated with adoption. In lower-income contexts where technological capacity is limited, regulatory clarity alone is unlikely to produce adoption gains but remains a necessary foundation.

- **Recognize that structural interventions are less likely to generate meaningful gains below a certain development threshold.**

In lower-middle-income economies, standard technology and regulatory mechanisms lose explanatory power considerably. Foundational capacity building, encompassing digital literacy, financial infrastructure, and basic institutional development, is a necessary precondition before technology or regulatory investments are likely to generate meaningful adoption gains.

- **Tailor strategies to NFT and DeFi markets separately.**

DeFi is more responsive to deep technological infrastructure and institutional maturity, particularly R&D intensity. NFT markets show stronger associations with digital marketplace maturity and consumer-facing ecosystems, consistent with the significance of digital commerce in 2SLS specifications and its directional association in baseline models. Treating Web3 as a homogeneous category risks applying the wrong tools to two technologies that work differently, and regulatory and investment frameworks should be designed with this distinction explicitly in mind.

10. Conclusions

This study set out to answer whether NFT and DeFi adoption are shaped by structural conditions or primarily by speculative and market-driven dynamics. The evidence across 105 countries points clearly toward the former. Adoption is not random. It is systematically shaped by three interrelated structural conditions: the technological capacity of an economy, the income level that conditions how effectively that capacity is associated with adoption gains, and the clarity of the crypto regulatory environment that is associated with amplifying or constraining it. FTRI emerges as the dominant correlate across all specifications. While it is equally associated with both NFT and DeFi adoption, the two technologies diverge in their secondary dependencies. National income conditions how effectively FTRI is associated with adoption gains, with FTRI effects weakening progressively across lower income groups and structural models losing considerable explanatory power in lower-middle-income economies. Crypto regulatory environments do not independently explain adoption but are associated with stronger FTRI effects where a defined framework exists. What matters is not whether regulation is permissive but whether it is clearly defined. Together these structural findings carry direct implications for how regulators, innovation agencies, and development authorities approach digital asset ecosystems. The structural correlate most strongly associated with adoption gains is not regulatory liberalization but investment in skills, R&D, and technological capacity. Context-sensitive strategies calibrated to development level matter more than uniform frameworks. NFT and DeFi markets require distinct approaches; DeFi is more strongly associated with deep technolog-

ical infrastructure and R&D intensity while NFT markets show stronger associations with digital marketplace maturity.

All findings should be interpreted as structural associations rather than causal effects. As blockchain technology evolves and Web3 markets mature, whether the primacy of FTRI persists remains an open question. What this study shows is that in the early stage of Web3 diffusion, technological capacity is not one factor among many. It is the foundation on which everything else rests.

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Abbreviations

The following abbreviations are used in this manuscript:

DAO	Decentralized Autonomous Organization
DC	Digital Commerce
DeFi	Decentralized Finance
FTRI	Frontier Technology Readiness Index
GDP	Gross Domestic Product
HC3	Heteroskedasticity-Consistent Covariance Estimator (Type 3)
ICT	Information and Communications Technology
IDT	Innovation Diffusion Theory
NFT	Non-Fungible Token
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
TOE	Technology-Organization-Environment Framework
VIF	Variance Inflation Factor
Web3	Web 3.0

Appendix A. Robustness and Sensitivity Analysis

Table A1. Log-Level Robustness Check: Baseline Models with Log-Transformed Dependent Variables (RQ1).

Variable	ln(NFT)	ln(DeFi)	ln(Combined)
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Constant	−6.3834 *** (2.234) [0.004]	−4.2027 *** (1.114) [<0.001]	−3.8226 *** (0.406) [<0.001]
Sig. Concerns/Restrictions	1.6850 (1.621) [0.299]	−0.5343 (0.549) [0.330]	0.0169 (0.292) [0.954]
Implicit Ban	1.4191 (1.567) [0.365]	−0.3129 (0.365) [0.391]	−0.0503 (0.282) [0.859]
Mostly Legal Investment	1.8023 (1.540) [0.242]	−0.3001 (0.371) [0.418]	0.1253 (0.266) [0.637]
Digital commerce	0.0002 (0.001) [0.778]	0.0001 (0.001) [0.943]	0.0002 (0.001) [0.772]
Global Crypto Adoption Index	0.1502 (0.872) [0.863]	1.3824 † (0.829) [0.095]	0.6434 ** (0.282) [0.022]
Internet penetration	0.0092 (0.007) [0.214]	0.0174 (0.011) [0.123]	0.0093 ** (0.004) [0.013]
FTRI	2.3857 *** (0.678) [<0.001]	1.6818 *** (0.413) [<0.001]	1.6995 *** (0.273) [<0.001]
Gini index	0.0153 (0.009) [0.107]	0.0141 (0.010) [0.155]	0.0087 ** (0.004) [0.016]
GDP growth	0.0378 (0.029) [0.200]	0.0190 (0.038) [0.620]	0.0128 (0.008) [0.117]
Model Fit Statistics			
R ²	0.470	0.330	0.721
Adj. R ²	0.420	0.266	0.695
Observations	105	105	105

Notes: OLS estimates with HC3-robust standard errors in parentheses; *p*-values in brackets. *** *p* < 0.01, ** *p* < 0.05, † *p* < 0.10. Dependent variables are natural log-transformed adoption indices. FTRI remains positive and significant across all specifications. Lower R² for ln(NFT) and ln(DeFi) reflects high skewness in the log-transformed variables (Jarque-Bera *p* < 0.001). Results confirm that the primacy of FTRI is not an artifact of linear scaling.

Table A2. Cook's Distance Robustness Check: Full Sample vs. Influential Observation-Trimmed Sample (RQ1).

Variable	NFT Full	NFT Trimmed	DeFi Full	DeFi Trimmed	Comb. Full	Comb. Trimmed
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Constant	−0.1256 ** (0.059)	−0.1836 *** (0.045)	−0.0513 (0.037)	−0.0263 (0.032)	−0.0884 ** (0.042)	−0.0807 ** (0.037)
Sig. Concerns/Restrictions	0.0481 (0.050)	0.1020 *** (0.034)	0.0038 (0.029)	−0.0155 (0.024)	0.0260 (0.036)	0.0201 (0.031)
Implicit Ban	0.0190 (0.052)	0.0729 ** (0.036)	−0.0081 (0.031)	−0.0063 (0.026)	0.0054 (0.038)	0.0185 (0.031)
Mostly Legal Investment	0.0514 (0.049)	0.0900 *** (0.033)	−0.0115 (0.029)	−0.0292 (0.026)	0.0200 (0.035)	0.0173 (0.031)
Digital commerce	0.0002 (0.000)	0.0003 (0.000)	0.0003 (0.000)	0.0006 *** (0.000)	0.0002 (0.000)	0.0004 *** (0.000)
Global Crypto Adoption Index	−0.0096 (0.066)	0.0303 (0.082)	0.0656 (0.067)	0.1122 ** (0.052)	0.0280 (0.047)	0.0581 (0.096)
Internet penetration	1.96 × 10 ^{−5} (0.001)	0.0008 † (0.000)	0.0006 (0.001)	0.0008 ** (0.000)	0.0003 (0.000)	0.0005 (0.000)
FTRI	0.3878 *** (0.063)	0.3254 *** (0.064)	0.3956 *** (0.068)	0.3573 *** (0.045)	0.3917 *** (0.053)	0.3658 *** (0.041)
Gini index	0.0011 (0.001)	0.0009 (0.001)	0.0006 (0.001)	0.0003 (0.000)	0.0008 † (0.000)	0.0007 (0.000)
GDP growth	0.0021 (0.002)	−0.0007 (0.003)	−1.48 × 10 ^{−5} (0.001)	0.0003 (0.002)	0.0010 (0.002)	0.0005 (0.002)
Model Fit Statistics						
R ²	0.708	0.716	0.851	0.861	0.851	0.849
Adj. R ²	0.68	0.687	0.837	0.847	0.837	0.834
Observations	105	96	105	98	105	98

Notes: OLS estimates with HC3-robust standard errors in parentheses. *** *p* < 0.01, ** *p* < 0.05, † *p* < 0.10. “Trimmed” columns exclude influential observations identified via Cook's Distance (threshold: 4/*n*). NFT: 9 observations removed (*n* = 96); DeFi: 7 removed (*n* = 98); Combined: 7 removed (*n* = 98). FTRI remains significant and stable across full and trimmed samples throughout.

Table A3. Variance Inflation Factors—Baseline OLS Model (RQ1).

Variable	VIF
Significant Concerns/Restrictions	4.59
Implicit Ban	2.54
Mostly Legal Investment	5.78
Digital commerce	1.27
Global Crypto Adoption Index	1.27
Internet penetration	3.49
FTRI	4.84
Gini index	1.40
GDP growth	1.21

Notes: VIF computed for baseline OLS model (N = 105). All regressors fall below VIF = 6, indicating no serious multicollinearity. The elevated condition number (2.06×10^3) is attributable to the intercept and does not affect the substantive regressors.

Table A4. Split-Sample Estimation: NFT Composite by Income Group (RQ2).

Variable	High-Income (N = 49)	Upper-Middle (N = 26)	Lower-Middle (N = 25)
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Intercept	0.1768 *** (0.038) [<0.001]	0.2053 *** (0.059) [<0.001]	0.1904 (0.256) [0.457]
FTRI	0.2943 *** (0.091) [0.001]	0.1399 (0.176) [0.426]	0.3527 (0.394) [0.371]
Digital commerce	5.451×10^{-5} (0.000) [0.627]	0.0003 (0.002) [0.913]	0.0011 (0.007) [0.864]
Regulatory Index	0.0036 (0.015) [0.809]	0.0112 (0.032) [0.724]	0.0289 (0.035) [0.410]
GDP growth	0.0025 (0.002) [0.170]	−0.0075 (0.010) [0.463]	0.0033 (0.014) [0.807]
Gini index	0.0005 (0.001) [0.586]	0.0016 (0.002) [0.531]	0.0032 (0.003) [0.293]
Global Crypto Adoption Index	0.8808 (0.569) [0.121]	0.6369 (1.274) [0.617]	−0.0902 (0.178) [0.612]
Internet penetration	0.0053 *** (0.002) [0.006]	0.0015 (0.003) [0.623]	−0.0015 (0.002) [0.460]
Model Fit Statistics			
R ²	0.761	0.533	0.475
Adj. R ²	0.721	0.351	0.259
F-statistic	14.93	1.680	0.649
Prob (F)	<0.001	0.177	0.711

Notes: OLS estimates with HC3-robust standard errors in parentheses; *p*-values in brackets. *** *p* < 0.01. Low-income group (N = 5) omitted. The upper-middle-income model (F *p* = 0.177) and lower-middle-income model (F *p* = 0.711) are jointly insignificant, indicating that the structural framework explains limited variation in these subsamples.

Table A5. Split-Sample Estimation: DeFi Composite by Income Group (RQ2).

Variable	High-Income (N = 49)	Upper-Middle (N = 26)	Lower-Middle (N = 25)
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Intercept	0.2467 *** (0.057) [<0.001]	0.2673 *** (0.030) [<0.001]	0.2260 ** (0.100) [0.024]
FTRI	0.3384 ** (0.138) [0.014]	0.2743 ** (0.109) [0.012]	0.1678 (0.188) [0.371]
Digital commerce	0.0003 (0.000) [0.551]	0.0007 (0.001) [0.439]	0.0001 (0.003) [0.959]
Regulatory Index	−0.0033 (0.020) [0.871]	−0.0074 (0.017) [0.668]	0.0199 (0.025) [0.423]
GDP growth	−0.0006 (0.003) [0.841]	0.0026 (0.004) [0.537]	−0.0005 (0.006) [0.931]
Gini index	0.0006 (0.001) [0.643]	0.0001 (0.001) [0.847]	0.0010 (0.002) [0.603]
Global Crypto Adoption Index	−0.0027 (1.074) [0.998]	0.5320 (0.405) [0.189]	0.1312 (0.094) [0.163]
Internet penetration	0.0026 (0.003) [0.336]	0.0003 (0.002) [0.864]	0.0009 (0.001) [0.480]
Model Fit Statistics			
R ²	0.796	0.806	0.759
Adj. R ²	0.761	0.730	0.660
F-statistic	7.597	6.117	5.153
Prob (F)	<0.001	<0.001	0.003

Notes: OLS estimates with HC3-robust standard errors in parentheses; *p*-values in brackets. *** *p* < 0.01, ** *p* < 0.05. Low-income group (N = 5) omitted. All three subsamples jointly significant (High: *p* < 0.001; Upper-Middle: *p* < 0.001; Lower-Middle: *p* = 0.003).

Table A6. Split-Sample Estimation: Combined Adoption Composite by Income Group (RQ2).

Variable	High-Income (N = 49)	Upper-Middle (N = 26)	Lower-Middle (N = 25)
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Intercept	0.2118 *** (0.024) [<0.001]	0.2363 *** (0.041) [<0.001]	0.2082 ** (0.084) [0.013]
FTRI	0.3164 *** (0.088) [<0.001]	0.2071 ** (0.099) [0.037]	0.2603 (0.222) [0.241]
Digital commerce	0.0002 (0.000) [0.421]	0.0005 (0.002) [0.764]	0.0006 (0.002) [0.766]
Regulatory Index	0.0002 (0.013) [0.990]	0.0019 (0.020) [0.922]	0.0244 (0.025) [0.332]
GDP growth	0.0010 (0.002) [0.664]	−0.0025 (0.006) [0.659]	0.0014 (0.008) [0.865]
Gini index	0.0005 (0.001) [0.526]	0.0008 (0.001) [0.554]	0.0021 (0.002) [0.346]
Global Crypto Adoption Index	0.4390 (0.383) [0.251]	0.5845 (0.812) [0.471]	0.0205 (0.079) [0.795]
Internet penetration	0.0039 *** (0.001) [0.005]	0.0009 (0.002) [0.614]	−0.0003 (0.001) [0.775]
Model Fit Statistics			
R ²	0.850	0.797	0.657
Adj. R ²	0.824	0.718	0.516
F-statistic	14.94	4.499	1.874
Prob (F)	<0.001	0.005	0.137

Notes: OLS estimates with HC3-robust standard errors in parentheses; p -values in brackets. *** $p < 0.01$, ** $p < 0.05$. Low-income group (N = 5) omitted. Lower-middle-income model jointly insignificant (F $p = 0.137$). FTRI positive and significant in high-income ($p < 0.001$) and upper-middle-income ($p = 0.037$) subsamples.

Table A7. Variance Inflation Factors—RQ2 Baseline Interaction Model.

Variable	VIF
FTRI	4.556
Internet penetration	3.322
Regulatory Index	1.783
Gini index	1.359
Digital commerce	1.266
Global Crypto Adoption Index	1.253
GDP growth	1.191

Table A8. Robustness Check: Disaggregated Regulatory Category Interactions (RQ3).

Variable	NFT Composite Index	DeFi Composite Index	Combined Adoption Index
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Baseline Effects			
FTRI	−0.1868 (0.126) [0.137]	0.2466 *** (0.090) [0.006]	0.0299 (0.097) [0.757]
Digital commerce	0.0029 (0.020) [0.884]	0.0075 (0.010) [0.465]	0.0052 (0.015) [0.729]
FTRI × Digital commerce	0.0007 (0.002) [0.746]	−0.0020 ** (0.001) [0.037]	−0.0006 (0.002) [0.685]
Mostly Legal Investment (vs. Explicit Ban)			
Mostly Legal Investment	−0.1527 (0.100) [0.125]	−0.0288 (0.047) [0.540]	−0.0908 (0.068) [0.182]
FTRI × Mostly Legal Inv.	0.5848 *** (0.139) [<0.001]	0.1584 (0.098) [0.106]	0.3716 *** (0.104) [<0.001]
Digital commerce × Mostly Legal Inv.	−0.0034 (0.020) [0.863]	−0.0052 (0.010) [0.611]	−0.0043 (0.015) [0.773]
Implicit Ban (vs. Explicit Ban)			
Implicit Ban	−0.0926 (0.133) [0.487]	−0.0174 (0.057) [0.758]	−0.0550 (0.088) [0.534]
FTRI × Implicit Ban	0.4694 + (0.275) [0.088]	0.1916 (0.153) [0.211]	0.3305 + (0.173) [0.056]
Digital Commerce × Implicit Ban	−0.0095 (0.026) [0.718]	−0.0103 (0.013) [0.413]	−0.0099 (0.016) [0.533]
Significant Concerns or Restrictions (vs. Explicit Ban)			
Significant Concerns/Restrictions	−0.1337 (0.093) [0.151]	−0.0465 (0.046) [0.309]	−0.0901 (0.067) [0.178]
FTRI × Sig. Concerns/Restrictions	0.5445 *** (0.150) [<0.001]	0.2361 + (0.123) [0.055]	0.3903 *** (0.124) [0.002]
Digital Commerce × Sig. Concerns/Restrictions	−0.0027 (0.020) [0.889]	−0.0057 (0.010) [0.579]	−0.0042 (0.015) [0.778]
Model Fit Statistics			
R ²	0.730	0.864	0.862
Adj. R ²	0.694	0.846	0.844

Table A8. *Cont.*

Variable	NFT Composite Index	DeFi Composite Index	Combined Adoption Index
	Coef. (SE) [<i>p</i>]	Coef. (SE) [<i>p</i>]	Coef. (SE) [<i>p</i>]
F-statistic	31.57	57.48	47.09
Prob (F)	<0.001	<0.001	<0.001
Observations	105	105	105

Notes: OLS estimates with HC3-robust standard errors in parentheses; *p*-values in brackets. *** *p* < 0.01, ** *p* < 0.05, † *p* < 0.10. Reference crypto regulatory category: Explicit Ban. Significant FTRI interactions for Mostly Legal Investment and Significant Concerns/Restrictions categories (NFT and Combined) indicate that FTRI effects are amplified relative to the Explicit Ban baseline in both permissive and restrictive regulatory environments. Elevated condition number (2.23×10^4) reflects collinearity among interaction terms; main FTRI interaction estimates are not materially affected.

Table A9. Robustness Check: Three-Way Interaction Model—FTRI × Regulatory Index × Digital Commerce (RQ3).

Variable	NFT Composite Index	DeFi Composite Index	Combined Adoption Index
	Coef. (SE) [<i>p</i>]	Coef. (SE) [<i>p</i>]	Coef. (SE) [<i>p</i>]
Main Effects			
FTRI	0.4247 ** (0.177) [0.017]	0.2756 *** (0.071) [<0.001]	0.3501 *** (0.115) [0.002]
Regulatory Index	−0.0074 (0.031) [0.811]	−0.0105 (0.014) [0.451]	−0.0090 (0.021) [0.669]
Digital commerce	0.0002 (0.001) [0.766]	0.0009 *** (0.000) [0.002]	0.0006 (0.000) [0.260]
Two-Way Interaction Terms			
FTRI × Regulatory Index	0.0191 (0.210) [0.927]	0.0644 (0.085) [0.449]	0.0418 (0.138) [0.762]
FTRI × Digital commerce	0.0013 (0.004) [0.763]	−0.0037 ** (0.002) [0.044]	−0.0012 (0.003) [0.689]
Regulatory Index × Digital commerce	−0.0004 (0.001) [0.611]	0.0001 (0.000) [0.813]	−0.0002 (0.001) [0.765]
Three-Way Interaction Term			
FTRI × Regulatory Index × Digital commerce	−0.0007 (0.005) [0.899]	0.0025 (0.002) [0.245]	0.0009 (0.004) [0.790]
Model Fit Statistics			
R ²	0.696	0.862	0.847
Adj. R ²	0.674	0.852	0.836
F-statistic	35.56	108.7	75.42
Prob (F)	<0.001	<0.001	<0.001
Observations	105	105	105

Notes: OLS estimates with HC3-robust standard errors in parentheses; *p*-values in brackets. *** *p* < 0.01, ** *p* < 0.05. All variables are mean-centered. The three-way interaction term is statistically insignificant across all outcome measures (*p* > 0.2), confirming the absence of joint higher-order moderation. The significant FTRI × Digital commerce term for DeFi (*p* = 0.044) does not replicate in the two-way specification (Table 4) or the disaggregated model (Table A8) and should not be treated as a robust finding.

Table A10. Variance Inflation Factors—Main RQ3 Two-Way Interaction Model.

Variable	VIF
Digital commerce	18.60 ‡
Digital commerce × Regulatory Index	18.32 ‡
FTRI	1.89
Regulatory Index	1.81
FTRI × Regulatory Index	1.26

Notes: VIF computed for the main RQ3 two-way interaction model (N = 105). ‡ VIF > 10 indicates problematic multicollinearity. High VIF values for Digital Commerce and its interaction term reflect collinearity driven by the distributional properties of the variable when crossed with a binary regulatory indicator. FTRI and its interaction with the Regulatory Index are unaffected (VIF < 2).

Table A11. Robustness Check: Log-Transformed Digital Commerce—RQ3 Two-Way Interaction Models.

Variable	NFT Composite Index	DeFi Composite Index	Combined Adoption Index
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Main Effects			
FTRI	0.3212 *** (0.053) [<0.001]	0.3333 *** (0.039) [<0.001]	0.3273 *** (0.038) [<0.001]
Regulatory Index	0.0026 (0.010) [0.796]	−0.0054 (0.009) [0.531]	−0.0014 (0.007) [0.843]
log(Digital commerce)	0.0250 ** (0.011) [0.019]	0.0376 *** (0.011) [0.001]	0.0313 *** (0.010) [0.002]
Two-Way Interaction Terms			
FTRI × Regulatory Index	0.0204 (0.056) [0.714]	−0.0361 (0.043) [0.406]	−0.0078 (0.043) [0.856]
log(Digital commerce) × Regulatory Index	0.0060 (0.010) [0.563]	0.0097 (0.011) [0.363]	0.0078 (0.010) [0.425]
Model Fit Statistics			
R ²	0.646	0.792	0.788
Adj. R ²	0.628	0.781	0.778
F-statistic	40.21	79.16	79.25
Prob (F)	<0.001	<0.001	<0.001
Observations	105	105	105

Notes: OLS estimates with HC3-robust standard errors in parentheses; *p*-values in brackets. *** *p* < 0.01, ** *p* < 0.05. All variables are mean-centered. Log transformation of digital commerce resolves the multicollinearity observed in the main specification, reducing VIF from 18.6 to 1.95. FTRI × Regulatory Index interaction terms remain statistically insignificant across all outcome measures, confirming that the null moderation result is not an artifact of multicollinearity. Lower R² relative to the main specification and non-normality in DeFi residuals support the original specification as the preferred model.

Table A12. Variance Inflation Factors—Log-Transformed Digital Commerce RQ3 Model.

Variable	VIF
FTRI	2.72
Regulatory Index	1.62
log(Digital commerce)	1.95
FTRI × Regulatory Index	1.88
log(DC) × Regulatory Index	1.83

Notes: VIF computed for the log-transformed RQ3 two-way interaction model (N = 105). Log transformation of digital commerce reduces VIF from 18.6 to 1.95, resolving the multicollinearity observed in the main specification. Mean VIF = 2.00, confirming resolution of multicollinearity under log transformation.

Table A13. Two-Stage Least Squares (2SLS) Robustness Check: Endogeneity Correction (RQ1).

Variable	NFT Composite	DeFi Composite	Combined Adoption
	Coef. (SE) [p]	Coef. (SE) [p]	Coef. (SE) [p]
Constant	−0.1257 (0.049) [0.010]	−0.0651 (0.031) [0.035]	−0.0954 (0.034) [0.005]
Sig. Concerns/Restrictions	0.0481 (0.044) [0.270]	−0.0046 (0.025) [0.853]	0.0217 (0.031) [0.480]
Implicit Ban	0.0190 (0.043) [0.661]	−0.0116 (0.026) [0.658]	0.0037 (0.031) [0.907]
Mostly Legal Investment	0.0513 (0.051) [0.311]	−0.0291 (0.025) [0.244]	0.0111 (0.033) [0.739]
Digital Commerce	0.0002 (0.000) [<0.001]	0.0003 (0.000) [<0.001]	0.0002 (0.000) [<0.001]
Global Crypto Adoption Index	−0.0097 (0.066) [0.882]	0.0450 (0.048) [0.349]	0.0176 (0.039) [0.648]
Internet penetration rate	0.0000 (0.001) [0.991]	−0.0001 (0.001) [0.846]	−0.0001 (0.001) [0.940]
FTRI	0.3886 ** (0.175) [0.026]	0.5147 *** (0.084) [<0.001]	0.4516 *** (0.105) [<0.001]
Gini Index	0.0011 (0.001) [0.187]	0.0009 (0.001) [0.087]	0.0010 † (0.001) [0.047]
GDP Growth	0.0021 (0.002) [0.338]	0.0009 (0.001) [0.461]	0.0015 (0.001) [0.287]
Model Fit Statistics			
R ²	0.708	0.843	0.849
Observations	105	105	105
First Stage F-stat	42.12	42.12	42.12

Notes: IV-2SLS estimates with robust standard errors in parentheses; *p*-values in brackets. *** *p* < 0.01, ** *p* < 0.05, † *p* < 0.10. Instrument: internet penetration rate in 2015 (World Bank). Partial F-statistic = 42.12 (*p* < 0.001), confirming instrument strength (Staiger & Stock, 1997). Reference crypto regulatory category: Explicit Ban. N = 105 countries.

Table A14. Quantile Regression Robustness Check: FTRI and Digital Commerce Across Adoption Distribution (RQ1).

	NFT Composite			DeFi Composite			Combined		
	Q25	Q50	Q75	Q25	Q50	Q75	Q25	Q50	Q75
FTRI	0.4255 ***	0.3837 ***	0.3867 ***	0.4050 ***	0.4348 ***	0.3984 ***	0.4494 ***	0.3926 ***	0.4386 ***
Digital Commerce	0.0002 **	0.0002 ***	0.0002 ***	0.0003 ***	0.0003 ***	0.0002 ***	0.0002 ***	0.0002 ***	0.0002 ***
Pseudo R ²	0.450	0.489	0.494	0.613	0.634	0.630	0.605	0.639	0.626
N	105	105	105	105	105	105	105	105	105

Notes: Quantile regression estimates. *** $p < 0.01$, ** $p < 0.05$. Only FTRI and Digital Commerce shown for brevity. All other control variables included; full results available on request. Full specification identical to baseline OLS model. N = 105 countries.

Table A15. FTRI Component Decomposition: Baseline RQ1 Models with Disaggregated FTRI Sub-components.

Variable	NFT Composite	DeFi Composite	Combined
FTRI_ICT	−0.119 ($p = 0.320$)	−0.070 ($p = 0.396$)	−0.095 ($p = 0.215$)
FTRI_Skills	0.222 *** ($p = 0.003$)	0.168 *** ($p = 0.001$)	0.195 *** ($p < 0.001$)
FTRI_RD	0.166 ** ($p = 0.039$)	0.265 *** ($p < 0.001$)	0.216 *** ($p < 0.001$)
FTRI_Industry	0.041 ($p = 0.473$)	−0.017 ($p = 0.700$)	0.012 ($p = 0.757$)
FTRI_Finance	0.110 ($p = 0.539$)	0.137 ($p = 0.119$)	0.123 ($p = 0.250$)
R ²	0.726	0.883	0.876
N	105	105	105

Notes: OLS estimates with HC3-robust standard errors. *** $p < 0.01$, ** $p < 0.05$. All other control variables included but not shown. Reference crypto regulatory category: Explicit Ban. FTRI component scores sourced from UNCTAD (n.d.). N = 105 countries.

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