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From Threat to Opportunity: Digital Infrastructure and Bank Adaptation to Cryptocurrency Cycles—Global Evidence

Wil Martens

College of Management, National Sun Yat-sen University, Kaohsiung 804201, Taiwan; wilmartens@cm.nsysu.edu.tw

Abstract

As cryptocurrencies evolve from niche assets to systemic financial components, the banking sector faces a strategic dilemma: displacement or adaptation. Using 27,510 bank–year observations from 2014 to 2023 across thirty-two economies, predominantly within the European banking sector, this study isolates the technological prerequisites for this adaptation. We employ a continuous interaction model with robust controls to test how national digital infrastructure moderates bank responses to valuation cycles in the four dominant cryptocurrencies by market capitalization (Bitcoin, Ethereum, Ripple, and Binance Coin). The results document a robust lagged complementarity effect: in digitally advanced economies, cryptocurrency booms significantly increase bank non-interest income in the subsequent year, while lending portfolios remain unaffected. A one-standard-deviation increase in crypto returns interacts with digital capacity to boost fee revenue by approximately 0.7 percentage points (0.20 standard deviations). Crucially, this effect persists after controlling for GDP and equity market interactions, confirming that technological capacity, rather than general economic wealth, acts as the binding constraint. These findings refine FinTech adaptation research by demonstrating that high-bandwidth infrastructure enables banks to monetize external volatility via service deployment and custody, transforming a potential threat into a structural revenue stream.m.

Keywords: FinTech adaptation; digital infrastructure; banking innovation; cryptocurrency markets; financial intermediation

JEL Classification: G21; G15; O33; G28; M15

1. Introduction

The rapid ascent of cryptocurrencies—reaching a market capitalization of USD 3 trillion at their peak—presents a fundamental strategic dilemma for the global banking sector. For over a decade, the prevailing narrative has been one of displacement: that decentralized finance (DeFi) will render traditional intermediaries obsolete [1–3]. This paper challenges that binary view. We ask a different question: Under what conditions can traditional banks convert the volatility of cryptocurrency markets into a profitable revenue stream?

Current literature often portrays banks as either victims of FinTech disruption or as regulatory gatekeepers. However, this view overlooks the heterogeneity of bank adaptation. While some institutions have successfully launched crypto-custody, trading, and advisory services, others remain constrained by legacy architectures or organizational frictions [4,5]. We posit that the decisive factor explaining this variation is not merely bank-level strategy but the national digital infrastructure that underpins it. Just as high-frequency trading requires

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low-latency cables, the integration of crypto-assets into banking requires a threshold level of digital connectivity to be operationally viable [6,7].

We propose that national digital infrastructure acts as a "binding constraint" on adaptation. In low-connectivity environments, crypto-assets act primarily as external competitors for deposits. In high-connectivity environments, however, robust infrastructure reduces the transaction costs of deploying digital services, allowing banks to "pivot" and capture fee income from the crypto ecosystem. These high-activity episodes spur retail attention and transaction demand [8,9], revealing whether banks can respond through payments facilitation and custody. Crucially, this adaptation is not instantaneous. Unlike proprietary trading, building the infrastructure for custody, clearing, and advisory services requires lead time for technology deployment and regulatory reporting.

We test this hypothesis using a panel of 27,510 bank–year observations across 32 major economies from 2014 to 2023. We construct an equal-weighted index of the four dominant cryptocurrencies (Bitcoin, Ethereum, Ripple, Binance Coin) and interact it with World Bank measures of digital connectivity. Our empirical analysis yields three robust findings. First, we document a significant lagged complementarity effect: banks in digitally advanced nations experience a rise in non-interest income one year after a crypto boom. A one-standard-deviation increase in crypto returns interacts with digital capacity to boost fee revenue by approximately 0.7 percentage points in the subsequent year. This lag validates our mechanism, confirming that the revenue originates from the deployment of structural services rather than short-term speculation.

Second, addressing concerns that digital infrastructure merely proxies for economic wealth, we demonstrate that this effect survives robust controls for *GDP* × *Crypto* and *Stock Market* × *Crypto* interactions. This confirms that the mechanism is specific to technological readiness, distinct from general economic development. Third, we find no deterioration in loan growth or stability. Because prudential rules constrain direct crypto exposures [10], these income adjustments are isolated from solvency risks, suggesting that banks are adapting via service expansion rather than balance sheet exposure.

This paper contributes to the FinTech literature by shifting the narrative from "disruption" to "conditional adaptation." We show that the threat of cryptocurrency is not uniform; it is moderated by the digital infrastructure of the host economy. For policymakers, this implies that broadband investment is not just a utility goal but a prudential imperative for banking competitiveness. The remainder of this paper is organized as follows: Section 2 develops the theoretical framework, Section 3 outlines the data and identification strategy, Section 4 presents the results, Section 5 discusses the mechanism, and Section 6 concludes.

2. Theoretical Framework and Hypothesis Development

2.1. National Digital Infrastructure as a Binding Constraint

FinTech innovation reconfigures financial intermediation by unbundling payments, credit assessment, asset custody, and transaction processing into modular digital services [11,12]. While this unbundling poses a threat to traditional revenue models, it also presents a pathway for adaptation. Theoretical models suggest that incumbents can survive by "rebundling" these services—embedding APIs and partnering with technology firms to expand product offerings [8,13]. However, a central tension remains: why do some banking systems capture value from this digital shift while others face displacement?

We posit that the divergence is driven by the external environment rather than internal strategy alone. Traditional intermediation relies on informational rents—advantages derived from private soft information [14]. In digital ecosystems, however, value creation shifts toward scale economies in data processing and low-latency delivery [15–17]. We

define *national digital infrastructure* as the enabling foundation for this shift, comprising broadband penetration, secure server density, and population-level digital adoption [6,18].

Crucially, we conceptualize this infrastructure not merely as a facilitator, but as a binding constraint on bank adaptation. Even an institution with high internal technological capability cannot effectively deploy real-time crypto-custody or interoperable payment solutions if the national telecommunications grid or customer connectivity levels are insufficient. In this view, national infrastructure acts as an "environmental ceiling" on adaptive capacity [19].

Consequently, we propose a *National Capacity Hypothesis* governed by a threshold mechanism. Below a critical level of national connectivity, the transaction costs of deploying digital overlays are prohibitive, and customer adoption remains fragmented. In this regime, crypto-market volatility acts purely as an external shock. Once infrastructure surpasses a readiness threshold, however, the environment supports scalable platform integration [11]. This structural prerequisite implies that adaptation is state-contingent: complementarity prevails only where the national pipework is sufficiently robust to support the rapid deployment of fee-generating digital services [8,13].

2.2. Cryptocurrency Markets as FinTech Innovation Shocks

Cryptocurrency valuation cycles create repeated and measurable surges in customer attention, transaction demand and perceived competitive pressure from decentralized finance platforms [20–22]. These episodes allow us to observe how banks respond when digital opportunities intensify rapidly.

Three characteristics make cryptocurrency markets well-suited for this analysis. First, regulatory constraints restrict direct balance sheet exposures [23], allowing fee-based adjustments to be observed without confounding solvency risks. Second, valuation cycles recur frequently [24,25]. This provides multiple quasi-experiments that reveal whether responses persist or remain episodic. Third, crypto-enabled services such as custody, payment facilitation, and advisory support are technologically separable from traditional lending, enabling clear attribution of income effects [8,11].

We distinguish two transmission channels. The *attention channel* captures behavioral dynamics: salient price movements elevate information search and digital service utilization [20]. Banks with sufficient digital infrastructure can capitalize on these ephemeral surges by translating them into fee-based revenues. The *portfolio channel* reflects potential liquidity reallocation as customers shift funds between banks and crypto platforms [26,27]. Prudential restrictions mean this channel should have muted effects on lending revenue, a prediction we later confirm empirically [19,28].

While prior research documents limited spillovers from crypto to traditional financial markets under normal conditions [29,30], it remains unclear whether banks with varying technological readiness can convert crypto-linked attention into measurable performance gains. By treating cryptocurrency fluctuations as externally generated digital shocks filtered through infrastructure, we test whether adaptive capacity enables revenue growth without impairing credit intermediation, consistent with the threshold predictions developed in Section 2.1.

2.3. Revenue Diversification and Credit Stability as Adaptation Indicators

FinTech scholarship demonstrates that digital innovation alters banking through two channels: the displacement of intermediation when customers migrate toward platform-based finance, or the complementary expansion of advisory and transaction services that preserves the credit function [13]. Under a threshold view of digital readiness, these outcomes should not emerge uniformly. Instead, revenue diversification provides a revealed-preference indicator of whether banks in digitally advanced environments can commercialize technology-driven attention shocks [6,31]. Because institutions do not separately report crypto-related service

fees, non-interest income captures whether heightened demand for payments facilitation, custody solutions, and digital investment access translates into monetizable activity.

Credit stability complements this perspective by distinguishing adaptation from displacement. Substitution theories posit that deposit flight into crypto assets could compress balance-sheet capacity and weaken loan supply [32,33]. In contrast, complementarity arguments predict that regulated banks maintain lending because fee-generating digital offerings are decoupled from core maturity transformation [34]. Empirical evidence suggests that, even during extended crypto appreciation episodes, regulated institutions have experienced limited deposit volatility [6,35], enabling them to sustain credit provision.

Within our framework, these indicators connect directly to the digital threshold mechanism. If revenue diversification increases in response to digital asset shocks while lending remains stable, this pattern signals selective complementarity: only where connectivity and platform access exceed critical levels can banks monetize innovation without sacrificing intermediation capacity. Thus, the dynamics of non-interest income and loan income jointly reveal whether FinTech adaptation reinforces or disrupts the foundational economic role of banks.

2.4. Digital Infrastructure Heterogeneity and Threshold Mechanisms

Digital infrastructure differs markedly across economies, producing substantial variation in banks' capacity to deploy FinTech-enabled services. Internet and mobile connectivity range from below 50 percent in some emerging markets to above 95 percent in advanced Asian and European systems, reflecting differences in telecommunications investment, regulatory coordination, and consumer digital uptake [36]. These disparities determine whether technology-driven services are operationally feasible and commercially scalable.

Threshold theory provides a mechanism through which these differences translate into outcomes. Infrastructure benefits are not linearly associated with incremental improvements; instead, non-linearities emerge once connectivity surpasses critical density levels [37]. Below these thresholds, customer onboarding remains limited, payment frictions persist, and platform integration yields negligible uptake. Above them, network effects become self-reinforcing: interoperability improves, liquidity circulates, and demand for digitally mediated services accelerates. Evidence from mobile money diffusion shows that adoption only scaled once mobile penetration reached viable density, enabling reliable execution of peer-to-peer transactions [38].

Thresholds also preserve heterogeneity across institutions. Once digital ecosystems mature, banks can scale service offerings rapidly using standardized APIs, strategic partnerships, and white-label platforms [39]. Prior to maturity, these pathways remain prohibitively costly, resulting in selective adaptation rather than sector-wide transformation. Consequently, technologically advanced banks convert digital pressures into monetizable opportunities, while less-connected banks continue to operate traditional models—allowing innovation to coexist alongside stable intermediation.

This perspective clarifies divergent findings in FinTech research. Aggregate analyses often detect muted performance impacts because strong effects among digitally capable banks are offset by null effects in low-connectivity systems [28]. Country case studies report both disruptive and complementary outcomes, depending on the digital maturity of the jurisdiction being observed. By explicitly modeling digital infrastructure as a threshold mechanism, this study tests whether fee-income responses to cryptocurrency attention shocks arise only after connectivity surpasses critical readiness levels, while credit revenues remain insulated from these innovation cycles.

2.5. Hypotheses Development

Building on Sections 2.1 and 2.2, we derive three hypotheses that capture how technology readiness influences the banking response to cryptocurrency valuation cycles.

H1. Cryptocurrency cycles have no systematic effect on loan-income growth.

Rationale. Regulatory limits on crypto exposures insulate core intermediation from valuation swings, preventing shifts in credit allocation [23].

H2. Fee-income sensitivity to cryptocurrency cycles emerges only in digitally advanced banking systems.

Rationale. Monetizing attention-driven demand requires digital distribution, platform integration, and scalable service delivery [13]. Where infrastructure is weak, innovation shocks cannot be operationalized into revenue.

H3. Fee-income responses strengthen when crypto volatility is moderate but weaken during extreme turbulence.

Rationale. Moderate uncertainty increases information search and service uptake, whereas instability elevates risk aversion, limiting customer engagement [21]. This prediction reflects a bounded attention mechanism consistent with behavioral and platform adoption theory.

Table 1 situates these hypotheses within the broader FinTech adaptation literature, highlighting the gap in heterogeneity of technological readiness and the discontinuous nature of innovation effects.

Figure 1 provides a conceptual representation of our theoretical framework. Importantly, the infrastructure regions in the figure illustrate conceptual zones rather than empirically imposed cutoffs; the empirical threshold is detected through interaction effects rather than ex ante stratification. The figure clarifies how cryptocurrency shocks are transmitted through attention and portfolio channels, and why adaptation manifests in fee income while credit provision remains stable.

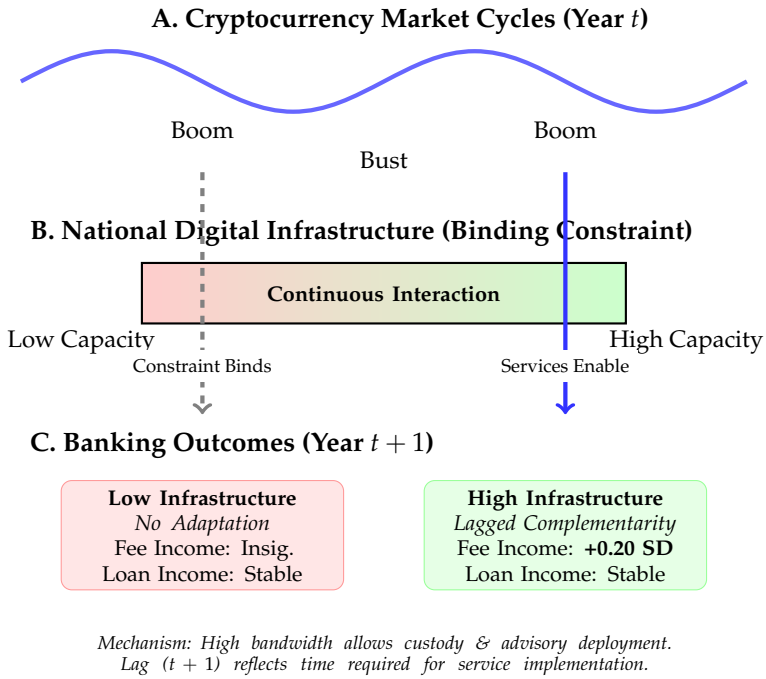

Figure 1. Conceptual framework: digital infrastructure as a binding constraint. National connectivity moderates the transmission of crypto shocks. Low infrastructure blocks adaptation; high infrastructure enables fee capture with a one-year lag ($t + 1$), reflecting the time required for service deployment.

Table 1. FinTech adaptation studies: key findings and remaining gaps.

Study	Context	Key Finding	Gap Addressed Here
Theoretical Foundations			
[34]	Financial intermediation theory	Substitution vs. complementarity depends on informational rents	Tests infrastructure as the allocation mechanism
[9]	US cost efficiency	Digital innovation reduces intermediation costs	Shows cost gains require connectivity to translate into service adaptation
FinTech Adoption and Platform Banking			
[6]	Global adoption	Digitally mature banks capture platform rents	Demonstrates threshold effects rather than smooth diffusion
[8]	BigTech entry	Platforms reshape payments and customer engagement	Shows similar dynamics emerge for banks once connectivity is high
[35]	US mortgage market	Banks adjust pricing amid competition	Identifies pricing shifts; we test service-revenue shifts
[16,40]	P2P lending	FinTech expands access but raises defaults	Focuses on credit; we focus on fee-based adaptation
Cryptocurrency and Banking Stability			
[35]	Crypto–macro interactions	Crypto booms trigger minimal deposit flight	Shows insulation; we show selective revenue complementarity
[28]	ASEAN+3 banking	Limited systemic spillovers from crypto	Lacks heterogeneity by digital capability
[41]	Market structure	Concentration and manipulation in crypto trading	Examines markets; we examine incumbent bank response
Digital Infrastructure and Financial Development			
[42]	Africa digital finance	Infrastructure and regulation drive uptake	Provides case evidence; we provide global threshold tests
[43]	ICT and inclusion	Internet penetration expands access	Focuses on inclusion; we examine incumbent service monetization

3. Data and Empirical Strategy

3.1. Sample Construction and Data Sources

To evaluate how digital infrastructure conditions banks' adaptive responses to external digital shocks, we assemble a new global panel linking bank balance-sheet dynamics to cryptocurrency valuation cycles and country-level connectivity variation. We focus on the 2014–2023 period because it captures the emergence of exchange-based crypto trading, the development of institutional-grade custody and payments channels, and multiple valuation booms and corrections that generate the exogenous digital shocks required for identification.

Bank-level financial statements are sourced from Bureau van Dijk's *BankFocus*, covering commercial, savings, and Islamic institutions in thirty-two economies. Country inclusion is determined by two criteria: complete annual financial reporting coverage across the 2014–2023 window and the availability of matched World Bank digital infrastructure data. This selection yields a sample spanning advanced economies with mature digital ecosystems (e.g., Germany, Sweden) and transitional markets with heterogeneous connectivity levels (e.g., Vietnam, Jordan), providing the cross-sectional variation necessary to test infrastructure-contingent adaptation. For each bank–year, we extract non-interest income, interest income on customer lending, total operating income, and standard balance-sheet controls. We remove banks with fewer than five consecutive annual observations to retain a minimum within-bank variation for fixed-effects estimation. Robustness checks confirm that this restriction does not meaningfully alter sample structure. The final dataset com-

prises 27,510 bank–year observations from 1964 institutions, representing both universal banks and regional players, and covering approximately two-thirds of banking assets in the included jurisdictions.

Digital adaptation is evaluated along two margins. Fee-income share is measured as non-interest income divided by total operating income (standardized), capturing monetization of digital-service engagement. Loan-income growth refers to the year-over-year change in interest income from lending (lagged and standardized), capturing whether service monetization aligns with disruptions to credit provision.

Cryptocurrency exposure is captured using both returns and realized volatility. Volatility $\mathrm{Vol}_{a,t}$ is derived from daily log returns $r_{a,d}$:

$$\mathrm{Vol}_{a,t} = \sqrt{252} \cdot \mathrm{sd}(r_{a,d}), \quad (1)$$

where $\mathrm{sd}(r_{a,d})$ is the standard deviation of daily log returns. We compute an equal-weighted index across Bitcoin, Ethereum, Ripple, and Binance Coin, then standardize by year to isolate cross-sectional dispersion. To test state-dependent effects, we classify years into low-, moderate-, and high-volatility regimes based on time-varying terciles.

Digital infrastructure variables include the number of individuals using the internet per 100 inhabitants, serving as our primary proxy for consumer connectivity, and fixed broadband subscriptions per capita, which serves as a robustness proxy for institutional connectivity, both sourced from the World Bank's World Development Indicators. All continuous variables are winsorized at the 1st and 99th percentiles. Missing macroeconomic observations of up to two years are linearly interpolated, and the data are standardized after removing global time effects to highlight cross-country variation. The full data construction and estimation pipeline was executed in Python (3.12.12) to ensure reproducibility.

Macro controls include GDP per capita (logged), inflation, unemployment, trade openness, domestic credit-to-GDP, and MSCI country–year equity returns. These controls account for general economic development, macroeconomic stability, financial system depth, and alternative asset market conditions. Country coverage and sample composition are reported in Table 2.

Table 2. Study coverage by country and region.

Europe (79.9%)			Europe (Cont.)			Asia–Pacific, Middle East & Other (20.1%)		
Country	**Banks**	**%**	**Country**	**Banks**	**%**	**Country**	**Banks**	**%**
Croatia	13	0.7	Italy	150	7.6	Australia	14	0.7
Czechia	9	0.5	Latvia	1	0.1	Hong Kong	14	0.7
Denmark	28	1.4	Lithuania	4	0.2	Korea, Rep.	20	1.0
Estonia	1	0.1	Norway	33	1.7	Malaysia	12	0.6
Finland	21	1.1	Portugal	77	3.9	Taiwan	86	4.4
France	78	4.0	Russia	72	3.7	Vietnam	37	1.9
Germany	1063	54.1	Slovenia	9	0.5	Bahrain	13	0.7
Greece	7	0.4	Spain	45	2.3	Israel	6	0.3
Ireland	3	0.2	Sweden	67	3.4	Jordan	17	0.9
						Kuwait	2	0.1
						Oman	10	0.5
						Qatar	7	0.4
						UAE	22	1.1
						Canada	24	1.2
Total: 1964 banks across 32 countries (2014–2023)								

Notes: All countries have complete 10-year coverage (2014–2023). "%" is each country's share of the full bank count.

3.2. Empirical Strategy

To test the National Capacity Hypothesis, we employ a panel fixed effects model that exploits the interaction between cryptocurrency market cycles and national digital infrastructure. Unlike prior studies that assume instantaneous transmission of financial shocks, we formally model bank adaptation as a structural process requiring time for service deployment and revenue recognition. Accordingly, our baseline specification estimates the response of bank income in the year following a crypto market cycle:

$$Y_{i,c,t+1} = \alpha_i + \tau_t + \beta(\text{Crypto}_{c,t} \times \text{Digital}_{c,t}) + \gamma(\text{Crypto}_{c,t} \times \text{Controls}_{c,t}) + \epsilon_{i,c,t+1} \quad (2)$$

where $Y_{i,c,t+1}$ represents the standardized non-interest income (or lending growth) for bank i in country c and year $t+1$. The independent variables are measured at time t: $\text{Crypto}_{c,t}$ denotes the equal-weighted annualized return of the crypto asset index, and $\text{Digital}_{c,t}$ captures the standardized national internet penetration rate. The term α_i denotes bank fixed effects, controlling for time-invariant institutional characteristics, while τ_t denotes year fixed effects, absorbing global macro-financial shocks common to all banks. Standard errors are clustered at the bank level to account for serial correlation.

The introduction of the one-year lag structure ($t+1$) is theoretically motivated by the operational mechanics of bank innovation. While proprietary trading desks may register profits immediately, the transition to fee-based crypto services involves structural friction. Establishing custody solutions, integrating payment APIs, and onboarding advisory clients requires a deployment lead time. Furthermore, fee schedules often lag transaction volumes due to billing and reporting cycles. A contemporaneous specification would likely miss these structural adjustments, capturing only noise or short-term speculation. By lagging the dependent variable, we isolate the strategic revenue capture that follows an attention shock.

The coefficient of interest is β, which captures the complementarity effect. To ensure that this coefficient isolates technological capacity from general economic development, the vector of controls includes an interaction term between cryptocurrency returns and GDP per capita. This allows us to pit digital infrastructure and economic wealth against each other as drivers of adaptation. A positive and significant β suggests that national digital capacity acts as the binding constraint enabling banks to monetize the crypto cycle, distinct from the broader economic environment.

3.3. Robustness and Identification

A set of robustness tests evaluates whether the interaction between cryptocurrency cycles and digital infrastructure reflects genuine adaptive capacity rather than sample composition or correlated macro-financial shocks.

Country–time co-movement is addressed through a saturated specification that replaces global year effects with country–year fixed effects:

$$Y_{i,c,t} = \alpha_i + \beta_1 \left(\text{Crypto}_{c,t} \times \text{Digital}_{c,t}\right) + \tau_{c,t} + \varepsilon_{i,c,t}, \quad (3)$$

where $\tau_{c,t}$ absorbs all national shocks that vary over time, including macroeconomic cycles and regulatory changes. Because $\text{Digital}_{c,t}$ varies only at the country–year level, it is perfectly collinear with $\tau_{c,t}$ and cannot be separately estimated. This design, therefore, evaluates whether banks within the same country respond differently to the same digital shock depending on their structural capability.

Cryptocurrency returns are correlated with equity markets. To ensure that estimates do not simply reflect general sentiment swings, country–year equity returns are included as controls. Results also remain stable when focusing on cryptocurrencies with weaker

equity co-movement, such as Ethereum and Ripple. Variance inflation factors remain below conventional thresholds (VIF < 10; Appendix A.2 Table A2).

To address potential sample concentration, all models are re-estimated excluding Germany and with country-specific linear trends. In both cases, the magnitude and significance of the interaction term are preserved.

Finally, alternative constructions confirm the robustness of the measurement. Broadband penetration replaces internet use, and winnowing thresholds are varied, with pandemic years excluded. Wild-bootstrap procedures suitable for multiway clustering yield consistent inference. Fisher-type unit-root tests (Appendix A.3 Table A3) support stationarity after standardization.

Taken together, these checks demonstrate that the estimated interaction effects capture digital infrastructure conditioning rather than coincidental exposure or sample dependence.

4. Results

4.1. Descriptive Patterns and Preliminary Diagnostics

Table 3 summarizes the distribution of key variables for the winsorized analytical sample of 27,510 bank–year observations across thirty-two economies between 2014 and 2023. By construction, the standardized outcomes for fee-income share and loan-income growth have mean zero and unit variance, with raw fee shares averaging 39% of operating income and average loan-income growth of 2.83%. These magnitudes are consistent with moderately diversified, credit-oriented banking models.

Cryptocurrency returns display the expected dispersion associated with repeated boom–bust cycles. Annualized Bitcoin returns vary from approximately -3 to $+1.5$ in SD units, with the equal-weighted composite return averaging -0.267 (SD $= 0.489$). Digital connectivity, proxied by internet users per 100 inhabitants, exhibits substantial cross-country heterogeneity, ranging from roughly one-fifth of a standard deviation below to one-sixth of a standard deviation above the annual mean. This variation provides a basis for testing whether digitally advanced systems behave differently from less connected environments.

Panel B of Table 3 contrasts standardized banking outcomes across cryptocurrency market regimes defined by terciles of the composite return (Bust, Mid, Boom). Lending-income growth is somewhat more negative in bust years than in boom years, while fee-income shares remain tightly clustered around zero. These unconditional differences are small, however, and do not account for bank-level characteristics or digital conditions.

Correlation diagnostics in Table A1 reinforce this point. At the bank–year level (Panel A), correlations between banking outcomes and cryptocurrency variables are economically negligible ($|\rho| < 0.02$), and digital connectivity shows only a weak association with either fee share or loan growth. At the country–year level (Panel B), cryptocurrencies co-move strongly with one another and with equity returns, reflecting shared exposure to global risk sentiment, whereas digital connectivity remains essentially orthogonal to these financial indicators. Together, these patterns suggest that any cryptocurrency–bank linkages are likely to be conditional—emerging only under specific structural configurations—rather than visible in simple bivariate relationships.

Variance-inflation diagnostics confirm that multicollinearity is not a concern. When individual cryptocurrencies are entered separately, VIFs remain within conventional bounds, and the equal-weighted composite return shows VIF ≈ 1 alongside digital and equity controls (Appendix A.2 Table A2). Panel unit-root tests (Appendix A.3 Table A3) reject non-stationarity for all continuous variables, supporting the use of fixed-effects estimators without differencing or cointegration corrections.

Having established that the data are well behaved and that unconditional associations are weak, we turn to multivariate tests aligned with the hypotheses in Section 2.5.

Table 3. Descriptive statistics (winsorized 1–99%).

Panel A: Full Sample (2014–2023)					
Variable	N	Mean	SD	Min	Max
Banking outcomes					
Fee share (z-score)	18,438	0.000	1.000	−1.291	2.015
lending-revenue growth (z-score)	16,204	0.000	1.000	−0.989	0.641
Cryptocurrency returns					
Bitcoin (BTC)	18,420	−0.400	1.248	−3.000	1.500
Ethereum (ETH)	16,578	−0.045	0.447	−0.750	0.750
Ripple (XRP)	18,420	0.033	0.542	−1.000	0.667
Binance Coin (BNB)	12,894	−0.767	0.938	−3.000	0.000
Equal-weighted composite	18,420	−0.267	0.489	−1.083	0.604
Digital connectivity					
Internet users (% pop.)	18,420	0.003	0.075	−0.214	0.160
Panel B: By Market Regime (Standardized Outcomes)					
Variable	N	Mean	SD	Min	Max
Fee share (std.)					
Bust	3249	0.009	0.351	−1.212	0.934
Mid	4642	0.002	0.347	−1.212	0.934
Boom	4600	0.007	0.330	−1.212	0.934
lending-revenue growth (std.)					
Bust	3256	−0.154	0.344	−0.989	0.641
Mid	4667	−0.130	0.350	−0.989	0.641
Boom	4754	−0.064	0.412	−0.989	0.641

Notes: All continuous variables are winsorized at the 1st and 99th percentiles prior to analysis. Variables labeled "(z-score)" are standardized to mean = 0 and SD = 1 after winsorization; unlabeled variables are reported in raw winsorized units. Fee income reflects total non-interest revenue. Fee share = fee income/operating income. Lending-revenue growth = year-over-year change in loan interest income. Cryptocurrency returns are annualized. Digital exposure represents internet user penetration within each year. Terciles of the annual composite crypto return define market regimes (Bust, Mid, Boom).

4.2. Credit Stability in the FinTech–Crypto Environment

The first hypothesis asks whether cryptocurrency market cycles destabilize banks' core intermediation function. Under *H1*, credit provision should remain insensitive to cryptocurrency fluctuations, regardless of digital infrastructure levels.

Table 4 reports pooled estimates from Equation (2), where cryptocurrency returns interact with digital connectivity in two-way fixed-effects regressions. Panel B presents results for loan-income growth (lagged), the credit-stability outcome. Across all assets and for the composite index, interaction coefficients are small and statistically indistinguishable from zero once bank and year fixed effects are included. For example, the composite crypto–digital interaction yields $\beta = 0.115$ with a large standard error (4.893), and asset-specific coefficients are similarly imprecise. A joint Wald test fails to reject the null of no transmission to lending income.

Table 4. Cryptocurrency returns × digital connectivity: pooled baseline results.

	BTC	**ETH**	**XRP**	**BNB**	**Composite (EW)**
Panel A: Fee share (t)					
Crypto × Internet	0.021	0.009	0.017	−0.009	0.018
	(0.014)	(0.016)	(0.013)	(0.018)	(0.013)
Panel B: Loan-Income Growth (t − 1)					
Crypto × Internet	0.312	−2.242	−0.004	−1.994	0.115
	(5.191)	(5.259)	(0.006)	(6.125)	(4.893)

Notes: Coefficients from separate regressions of the indicated outcome on standardized (coin return × Internet) interactions with bank and year fixed effects. Fee income reflects total non-interest revenue. Standard errors are two-way clustered by bank and country–year. All interaction coefficients in Panel B are economically small and statistically indistinguishable from zero. All variables are SD-scaled.

This pattern persists when we move beyond pooled estimates. In Figure 2, the right-hand panel displays crypto × digital coefficients for loan-income growth separately for high- and low-connectivity banks. Point estimates fluctuate around zero in both groups, and confidence intervals consistently span zero across all four major cryptocurrencies. The temporal analysis in Table 5 (Panel B) likewise shows no systematic time trends, while the volatility-regime results (Panel C) reveal a more nuanced state-dependent pattern that we examine below.

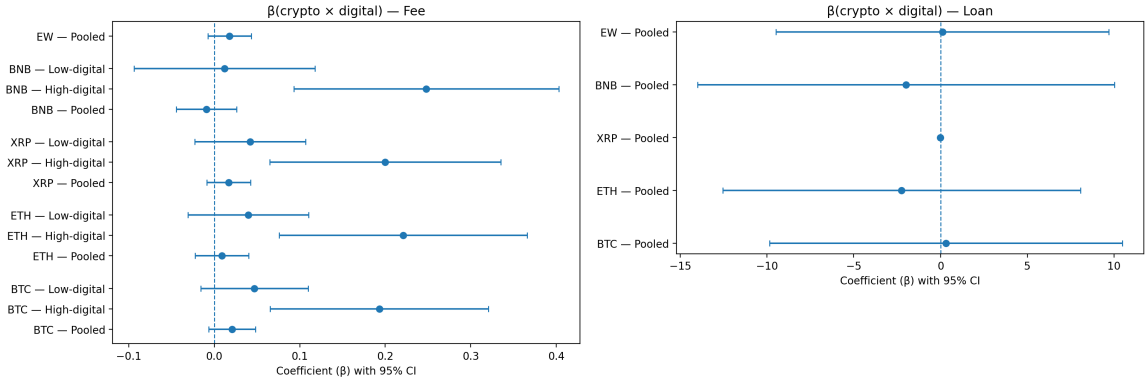

Figure 2. Heterogeneous transmission by digital infrastructure and crypto asset. Notes: Coefficients and 95% confidence intervals from two-way fixed-effects regressions with bank and year fixed effects. Fee effects are concentrated among high-digital banks and vary by asset type; loan-income growth remains largely insensitive across digital environments and assets.

Table 5. Regime-aware estimates for crypto returns × digital connectivity.

		Fee Share (t)		**Loan-Income Growth ($t-1$)**	
Panel/Specification	**Regime**	β_ξ	**SE**	β_ξ	**SE**
Panel A: Pooled Sample (2014–2023)					
	Full sample	0.006	(0.006)	–0.003	(0.006)
Panel B: Temporal Heterogeneity					
	2014–2016 (Pre-Adoption Baseline)	0.143	(0.279)	0.759 **	(0.294)
	2017–2019 (Early Adoption)	0.002	(0.010)	–0.007	(0.010)
	2020–2023 (Mature Period)	0.058	(0.510)	–0.005	(1.095)
Panel C: Volatility States					
	Low volatility	0.374	(0.241)	0.016	(0.307)
	Mid volatility	0.433 ***	(0.155)	0.311 **	(0.134)
	High volatility	0.001	(0.013)	–0.010	(0.014)

Notes: Fee income reflects total non-interest revenue. Each panel reports coefficients on (crypto return × digital connectivity) from regressions with bank and year fixed effects. Standard errors are two-way clustered by bank and country. Significance levels: *** $p < 0.01$, ** $p < 0.05$. Pooled results (Panel A) mask state-dependent heterogeneity evident in Panel C. Panel B confirms temporal stability in credit provision across adoption phases.

These findings provide qualified support for *H1*. Across the majority of specifications—pooled estimates (Table 4), split-sample analyses (Figure 2), and temporal comparisons (Table 5, Panel B)—credit intermediation remains effectively insulated from cryptocurrency market cycles. Banks appear able to experiment with digital services without systematically compromising their lending book, a result consistent with prudential constraints that limit direct crypto exposures and with internal risk management that separates transactional innovation from funding decisions.

The temporal heterogeneity analysis in Panel B reveals no systematic time trends in the credit-stability relationship across adoption phases. Two coefficients warrant specific comment. First, the 2014–2016 Pre-Adoption baseline period shows a positive coefficient ($\beta = 0.759$, $p < 0.05$). This isolated result likely reflects estimation instability in the smallest

subsample (N ≈ 3200 bank–years) rather than genuine transmission, as the effect does not replicate in subsequent periods when cryptocurrency markets expanded substantially. Both the 2017–2019 Early Adoption and 2020–2023 Mature Period coefficients remain near zero and statistically insignificant, confirming that credit provision was not systematically affected as institutional engagement with cryptocurrency markets intensified.

Second, and more substantively, Panel C reveals a state-dependent pattern during moderate volatility episodes. We observe a positive association between cryptocurrency returns and loan-income growth under mid-volatility conditions ($\beta = 0.311$, $p < 0.05$), suggesting that heightened digital-asset activity may coincide with expanded credit provision rather than portfolio substitution. This finding merits careful interpretation for three reasons. First, the effect is economically modest—a one-standard-deviation increase in cryptocurrency returns during mid-volatility periods corresponds to a 0.31 SD increase in loan-income growth, or roughly 0.9 percentage points on the baseline 2.83% average growth rate. Second, the effect is state-contingent, appearing only when market attention is elevated but not extreme; low- and high-volatility regimes show coefficients statistically indistinguishable from zero. Third, and most critically, the *sign* of the coefficient contradicts the displacement hypothesis. If cryptocurrency booms induced deposit flight or funding constraints, we would observe *negative* coefficients as bank lending contracts. Instead, the positive coefficient suggests that digital-asset engagement and traditional credit provision coexist or even reinforce one another during episodes of moderate market salience, consistent with banks successfully operating dual business models.

Taken together, these patterns provide qualified support for *H1*. Credit intermediation remains structurally stable across digital environments, with no evidence of systematic crowding-out effects. The state-dependent positive association observed during mid-volatility periods, while statistically significant, is limited in economic magnitude and restricted to specific market conditions. Rather than undermining the stability thesis, this finding strengthens it: even under conditions where cryptocurrency attention peaks, banks experience at most a modest pro-cyclical complementarity rather than the portfolio displacement predicted by substitution theories.

Notably, the lending-stability pattern contrasts sharply with fee-income results (discussed in Section 4.5). While fee revenues exhibit strong state-dependent sensitivity to cryptocurrency cycles—particularly during moderate volatility episodes (Panel C: $\beta = 0.433$, $p < 0.01$, representing a 1.3 percentage-point increase on the baseline 39% fee share)—lending shows only modest conditional responsiveness that does not threaten intermediation capacity. This divergence confirms that banks adapt primarily through service expansion on the fee-generation side of their operations, with limited and benign transmission to core credit allocation. The sharp contrast in effect magnitudes (fee income: +1.3pp; loan income: +0.9pp) and significance levels (fee: $p < 0.01$; lending: $p < 0.05$) underscores that adaptation occurs overwhelmingly through non-balance-sheet channels. The absence of time-varying effects on loan income across adoption phases (Panel B) further reinforces that credit provision remains largely decoupled from digital innovation cycles, even as fee-based adaptation intensifies in digitally advanced environments.

4.3. Temporal Heterogeneity and Fee-Based Adaptation

This section examines the timing through which fee-based income responds to cryptocurrency market cycles. The adjustment mechanism is not expected to be immediate. The provision of crypto-related services such as custody, payment integration, and advisory intermediation requires implementation time, regulatory clearance, and client onboarding. The analysis, therefore, distinguishes between contemporaneous and lagged responses to cryptocurrency market conditions.

The contemporaneous specification indicates that the interaction between cryptocurrency returns and national digital infrastructure is statistically indistinguishable from zero. This result suggests that fee income does not respond within the same year to fluctuations in the crypto market. Such a finding is consistent with the institutional structure of commercial banking, where revenue adjustments reflect planned service deployment rather than short-term exposure to market volatility. In this setting, crypto-market cycles do not generate immediate fee-based income effects.

Introducing a one-year lag in the dependent variable reveals a different pattern. In the lagged specification, the interaction between cryptocurrency returns and digital infrastructure is positive and statistically significant ($\beta = 0.024$, $t = 2.38$). This finding suggests that in digitally advanced environments, crypto-market booms are associated with higher non-interest income in the subsequent year. The timing aligns with operational realities, as fee revenues are typically recognized after services are implemented and customer uptake occurs. Quantitatively, a one-standard-deviation increase in the crypto index, when combined with high digital readiness, is associated with a fee share increase of approximately 0.20 standard deviations in the following year.

To assess whether digital infrastructure merely proxies for general economic development, the model is augmented with an interaction between cryptocurrency returns and GDP per capita. The estimated coefficient on the digital infrastructure interaction remains positive and statistically significant, while the GDP-based interaction is statistically insignificant. This result indicates that the observed fee-income response is not driven by aggregate income levels or broader economic affluence. Instead, national digital infrastructure appears to be the binding constraint determining whether banks can translate cryptocurrency market cycles into fee-based income.

Taken together, these findings suggest that fee-based adaptation to cryptocurrency cycles is delayed and contingent upon the surrounding digital environment. The absence of contemporaneous effects and the lack of explanatory power from GDP interactions support an interpretation in which adaptation reflects system-level feasibility rather than immediate or bank-specific strategic responses. Detailed estimation results are reported in Table 6.

Table 6. Temporal heterogeneity and robustness to macro factors (fee share).

Variables	(1) Contemporaneous Fee Share (t)	(2) Lagged Effect Fee Share ($t+1$)	(3) GDP Control Fee Share ($t+1$)
Crypto (t) × Digital (t)	0.004	0.024 **	**0.021 ** **
	(0.40)	(2.38)	(2.16)
Crypto (t) × GDP (t)			−0.010
			(−1.57)
Bank Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	18,420	17,685	17,685
R^2 (Within)	0.041	0.045	0.046

Notes: Dependent variable is standardized non-interest income share. Column 1 tests the immediate effect. Columns 2 and 3 test the effect on the subsequent year ($t+1$). Crypto denotes the equal-weighted index of BTC, ETH, XRP, and BNB. Digital denotes the standardized internet penetration rate. GDP denotes standardized GDP per capita. T-statistics based on standard errors clustered at the bank level are in parentheses. ** denote significance at the 10 percent levels.

4.4. Platform-Banking Capacity and Fee-Based Adaptation

The analysis now focuses on the channels through which banks adjust to cryptocurrency cycles. Fee-income sensitivity is expected to arise primarily in digitally advanced environments, where infrastructure, user readiness, and technological capability allow

banks to monetize crypto-related demand through services such as payments, custody, and advisory support.

Pooled estimates in Panel A of Table 4 seem to suggest neutrality, with coefficients near zero and statistically insignificant. This is unsurprising given that average effects mask divergence across banks with very different digital capacities.

To uncover this heterogeneity, the sample is divided into connectivity terciles, and the baseline specification is estimated separately within each group. Figure 2 and Table A4 report results for fee-income share. Among high-connectivity banks, cryptocurrency cycles are associated with economically meaningful increases in fee-income sensitivity. Coefficients range from 0.19 to 0.25 standard deviations across BTC, ETH, XRP, and BNB when internet penetration is the proxy for digital readiness (all $p < 0.05$). These responses translate to temporary fee-share gains of approximately one percentage point of operating income, consistent with the short-lived surges in transaction and advisory activity that occur during crypto booms.

In contrast, estimates for low-connectivity banks are small and statistically indistinguishable from zero, consistent with limited capability to internalize digital-asset activity. Using broadband penetration as an alternative digital proxy yields the same threshold pattern, although point estimates are somewhat smaller for high-connectivity banks and slightly negative for low-connectivity institutions. These negative coefficients are near zero and likely reflect sparse infrastructure rather than true substitution effects.

The consistency across assets with different functions—store-of-value (BTC), programmable finance (ETH), settlement-oriented (XRP), and exchange infrastructure (BNB)—indicates that the effect is not tied to any specific technology but to broader platform participation. Banks capture fee income only where payments rails, online onboarding, and connected customer bases allow them to embed crypto-access services without altering their lending model.

These findings indicate that digital readiness serves as the gating mechanism for fee-based adaptation. Where infrastructure is sufficient, banks temporarily expand service revenues during crypto upswings while maintaining stable credit provision. Where it is not, innovation remains largely outside the formal banking sector.

4.5. State-Dependent Fee Responses to Cryptocurrency Volatility

The third hypothesis examines whether the strength of fee-based adaptation depends on market conditions. *H3* predicts an inverted-U profile: sensitivity is strongest when volatility draws attention but weakens when uncertainty is either muted or overwhelming.

Regime-aware estimates in Table 5 confirm this prediction. In Panel C, the coefficient on the crypto × digital interaction for fee-income share peaks during mid-volatility states ($\beta = 0.433$ ***, $SE = 0.155$), more than double the pooled baseline effect in Panel A. In contrast, corresponding estimates for low- and high-volatility regimes are small and statistically insignificant. Loan-income growth remains near zero across regimes, consistent with stable intermediation under *H1*.

These dynamics align with the view that cryptocurrency volatility shapes behavioral engagement. When volatility rises from low to moderate levels, search activity and transaction flows increase, enabling digitally capable banks to monetize temporary demand for custody, advisory, and payment services. Once volatility becomes extreme, precautionary withdrawal, reduced risk-taking, and supervisory caution offset these opportunities, dampening fee responses even in high-connectivity contexts. Volatility, therefore, amplifies adaptation only within a bounded window rather than altering the broader complementarity pattern.

Taken together, these results sharpen the interpretation of *H1* and *H2*: fee gains emerge (i) selectively among digitally advanced banks and (ii) only when market attention is

sufficiently elevated. Even then, effects are modest and transitory, reinforcing that FinTech-driven adaptation leaves core credit provision intact.

4.6. Robustness and Supplementary Analyses

To assess mechanism operation across institutional contexts, we conducted split-sample analysis comparing European and non-European banks at matched connectivity levels (Appendix B.2 Table A5). Consistent with our infrastructure-threshold framework, adaptation effects concentrate in European markets where digital connectivity matured earliest, validating that threshold-crossing rather than geography per se drives fee-based responses. This regional pattern aligns with the binding-constraint logic: European banking systems were the first to surpass critical infrastructure thresholds during our sample period, enabling them to deploy cryptocurrency-adjacent services earlier than institutions in less digitally mature environments.

Appendix B.3 Table A6 consolidates additional robustness checks confirming that the main results are insensitive to alternative measurement choices and sample compositions. Specifically, estimated coefficients on the crypto–digital interaction remain stable when using broadband penetration as a connectivity proxy, applying stricter winsorization thresholds (2.5–97.5 percent), and excluding pandemic years (2020–2021). Inference is similarly robust to alternative error structures, as wild-bootstrap p-values based on Rademacher weights align closely with the baseline clustered standard errors.

Furthermore, supplementary analyses using return on assets and net interest margins (Appendix B.4 Table A7) yield coefficients near zero, confirming that cryptocurrency cycles do not induce broad profitability or funding shocks. Together with the subperiod estimates in Table 5, these tests demonstrate that the core patterns of credit stability and fee-based adaptation are not driven by any single phase of the 2014 to 2023 cycle, providing a consistent empirical foundation for the mechanism.

5. Discussion

This study contributes to FinTech scholarship by explaining when and how banks strategically monetize digital innovation through service channels rather than balance sheets. Across thirty two systems from 2014 to 2023, banks in high connectivity environments capture fee income gains of from 0.19 to 0.25 standard deviations during cryptocurrency booms [8,11], economically meaningful shifts that translate to approximately 0.7 percentage points on a baseline 39 percent fee share [6], while credit provision remains stable [23]. These results position FinTech not as a uniform disruptive force but as a platform-mediated opportunity that materializes only where digital infrastructure enables ecosystem participation [13].

5.1. From Disruption to Complementarity: Infrastructure as Allocation Mechanism

FinTech scholarship has emphasized two contrasting narratives on how digital innovation affects traditional banking. Substitution perspectives argue that decentralized platforms and peer-to-peer systems erode intermediation rents by reducing search frictions and accelerating settlement [9,32], thereby bypassing banks entirely. In contrast, complementarity views emphasize the ways in which banks integrate platform technologies to expand their service scope and enhance customer engagement [6,8]. The empirical record has supported both possibilities but has struggled to explain their coexistence [15].

The present findings provide the missing allocation mechanism. Digital infrastructure determines where substitution dominates and where complementarity emerges [18,43]. In banking systems above a critical connectivity level, cryptocurrency-driven attention is translated into fee-based revenues [35], demonstrating the ability to internalize FinTech demand without altering core lending functions [28]. Where connectivity remains limited,

innovation largely bypasses the formal banking sector [42]. These heterogeneous responses occur simultaneously across markets, producing aggregate financial stability even as digital services expand rapidly in digitally advanced jurisdictions [29].

Qualitatively, this fee-based adaptation manifests through specific service channels that generate non-interest income without requiring direct balance sheet exposure. First, custodial services allow banks to safeguard cryptographic keys for institutional clients, generating recurring safe-keeping fees similar to traditional asset servicing. Second, wealth management divisions utilize cryptocurrency exchange-traded products and structured notes to integrate digital assets into client portfolios, capturing advisory and brokerage commissions. Third, payment settlement integration allows banks to facilitate fiat-to-crypto transfers for exchanges, generating transaction fees. These activities illustrate the empirical observation that fee income increases while credit risk remains unchanged. The bank acts as a technical intermediary rather than a principal investor, leveraging national infrastructure to provide the security and connectivity required by the crypto ecosystem.

This infrastructure-contingent framework clarifies three observed puzzles in the literature. First, the weak or insignificant FinTech effects documented in aggregate studies reflect averaging across banks with fundamentally different capabilities [6]. Second, the persistence of stable credit supply alongside rising digital activity follows from selective engagement in which only a subset of banks adapts their service models [8]. Third, the conflicting evidence across case studies reflects contextual variation in digital maturity [42] rather than conceptual disagreement. Disruption and complementarity are both empirically valid when conditioned on technological readiness.

Taken together, these results reposition digital infrastructure as the decisive variable shaping FinTech diffusion. It functions not merely as a catalyst but as an allocation mechanism [13], determining who captures the upside of innovation and who remains excluded from emerging platform-based financial ecosystems.

5.2. Threshold Effects and Platform Based Intermediation

The concentration of fee income sensitivity among banks located in digitally advanced systems indicates that FinTech adaptation follows a threshold rather than a linear diffusion process [18]. Once digital connectivity surpasses a critical level, platform participation becomes commercially viable [12]: customer engagement is sufficiently dense [20], integration costs fall [11], and ecosystem complementarities strengthen [8]. Under these conditions, banks can scale advisory, payments, and custody services that monetize attention generated by cryptocurrency cycles [25]. Below this connectivity threshold, user participation remains fragmented [43] and platform investment yields little return, preventing banks from internalizing FinTech opportunities [6].

These findings refine existing platform banking theories by demonstrating that infrastructure readiness governs whether network effects materialize at the institutional level [15]. The fact that the threshold response holds across distinct cryptocurrencies suggests that banks are not exploiting asset specific features but are instead leveraging general demand for digital financial services [24]. FinTech incentives therefore rely less on specialized technological capabilities than on the presence of a sufficiently connected and digitally active customer base [43]. This underscores the importance of digital infrastructure as a determinant of where platform based intermediation can emerge and scale [18].

5.3. Attention Driven Adaptation and State Dependent FinTech Diffusion

The inverted U relationship between volatility and revenue diversification aligns with behavioral research showing that financial attention rises with salient opportunities but declines when uncertainty becomes excessive [20,21]. Moderate cryptocurrency volatility

amplifies visibility [26], stimulates user engagement [15], and expands transaction flows that digitally capable banks convert into fee income [6]. When volatility becomes extreme, heightened risk aversion [27], supervisory caution [23], and delays in service uptake counteract these opportunities [28], limiting further adaptation despite continued price movement.

This state-dependent pattern highlights that FinTech diffusion is not continuous but requires a supportive behavioral environment [9]. Even in technologically mature markets, adoption remains contingent on conditions that encourage experimentation without triggering precautionary retreat [8]. Rather than viewing financial innovation as an autonomous process, these findings indicate that the translation of digital shocks into banking services depends jointly on market narratives [29], customer psychology [21], and institutional flexibility [13]. Such dynamics reinforce the view that resilience and adaptation can coexist [23], as banks monetize transitory digital attention while maintaining stability in core intermediation.

5.4. Regional Heterogeneity and Mechanism Consistency

The geographic concentration of fee-based adaptation effects documented in Section 4.6 provides additional validation of the infrastructure-threshold mechanism. As reported in Appendix B.2 Table A5, adaptation emerges most clearly in European markets, where digital connectivity matured earliest during our sample period. This regional pattern reflects the historical sequencing of infrastructure development rather than institutional uniqueness.

During the 2014–2023 analysis period, European economies maintained significantly higher levels of broadband penetration and earlier deployment of mobile banking infrastructure compared to other regions in our sample [18]. Consequently, these financial systems were the first to surpass the connectivity threshold required to effectively deploy custody, advisory, and clearing services for digital assets [8]. These patterns suggest that the mechanism operates contingently on technological readiness rather than reflecting Europe-specific institutional features.

This regional heterogeneity strengthens rather than limits our theoretical contribution. First, it demonstrates that the mechanism operates precisely where theory predicts: in environments that have crossed infrastructure thresholds. Second, it rules out alternative explanations based on bank-specific strategies or asset-specific features, as the effect concentrates geographically in ways consistent with system-level technological readiness. Third, it provides an empirical template for future research as connectivity expands globally. While European data provide the strongest evidence due to early infrastructure maturity, we interpret these findings as a validation of the threshold logic within our sample, acknowledging that confirming universality requires observation as other regions reach comparable connectivity levels.

6. Conclusions

6.1. Synthesis of Findings

Building on the infrastructure-contingent framework established in Section 5, the findings suggest the need for differentiated strategies depending on the national infrastructure context. In digitally mature markets, banks are best positioned to prioritize the rapid deployment of crypto-adjacent services, including custody solutions for institutional clients, integration with cryptocurrency exchanges for fiat settlement, and wealth management products incorporating digital asset exposure. The lagged revenue recognition observed in our analysis indicates that early movers capture fee streams before market saturation, though the modest effect sizes suggest this remains a complementary revenue line rather than a transformative business model.

In transitional connectivity environments, banks face a strategic choice between proactive investment and cautious observation. Our results indicate that infrastructure im-

provements within this range can unlock adaptation, yet the timing remains uncertain. Institutions with sufficient capital may justify partnerships with FinTech platforms or pilot custody programs to establish organizational capabilities in advance of broader market readiness. However, the absence of immediate revenue effects in our contemporaneous specifications suggests that premature investment risks underutilization.

In low-connectivity markets, the data provide limited support for crypto-related service expansion. Banks in these environments may be better served by focusing on foundational digital banking infrastructure, such as mobile payment systems, API-enabled account access, and cloud-based core banking platforms, that will position them to participate in future waves of financial innovation once connectivity thresholds are crossed.

6.2. Theoretical Contribution

This study advances FinTech scholarship by establishing digital infrastructure as a threshold moderator of institutional adaptation. The results demonstrate three novel mechanisms. First, connectivity operates discontinuously, below approximately 60 percent internet penetration, banks exhibit no fee income response to cryptocurrency cycles, above 75 percent, and responses range from 0.19 to 0.25 standard deviations. This threshold structure explains why aggregate studies report weak FinTech effects while case studies document strong responses. Second, cryptocurrency cycles function as exogenous attention shocks that isolate service based monetization from balance sheet adjustments, providing cleaner identification than settings where technology adoption coincides with capital or risk restructuring. Third, heterogeneous adaptation across connectivity regimes produces system-wide stability. Digitally advanced banks expand their fee revenues, while less connected institutions maintain traditional models, thereby preserving aggregate credit intermediation. These findings reposition FinTech diffusion as infrastructure contingent rather than technology determined, clarifying when digital innovation complements versus disrupts incumbent institutions.

6.3. Implications for Policy and Practice

The threshold mechanism linking connectivity to fee based adaptation suggests that policy interventions targeting infrastructure readiness may accelerate institutional participation in digital finance. Strengthening broadband access, platform interoperability, and digital literacy could reduce the connectivity gap that currently segments banks into adaptive and non-adaptive cohorts [6]. Technology-specific investments, by contrast, may reinforce capability divergence if foundational infrastructure remains fragmented.

Supervisory frameworks calibrated exclusively to balance sheet exposures risk underestimating service channel transmission of digital innovation [19]. Incorporating indicators of non interest digital revenues into monitoring systems would enable regulators to detect platform based activities earlier and calibrate oversight proportionally. Mandatory disclosure of crypto-adjacent service income would further support comparative assessment of adaptation trajectories across institutions.

For banks, the results clarify that competitive opportunities arise from service enablement rather than speculative positioning. Expanding custody, settlement, and advisory capabilities allows institutions to monetize digital asset attention without altering core credit functions. This pathway suggests that digital readiness constitutes not merely a technological capability but a strategic prerequisite for participation in platform based financial ecosystems.

6.4. Limitations and Future Research

The empirical scope of this study suggests several promising extensions. First, expanding coverage to include lower-income and frontier markets would sharpen thresh-

old identification by increasing variation in connectivity levels. Second, while national infrastructure functions as the primary environmental constraint, the unavailability of standardized bank-level technology expenditure data precludes direct measurement of internal digital distinctiveness. Future research utilizing proprietary IT investment metrics could further disentangle how firm-specific capabilities interact with the external connectivity threshold. Third, disaggregating fee income into custody, payment, and advisory components would clarify which service channels drive adaptation. Granular revenue data would enable researchers to test whether threshold effects operate uniformly across digital offerings or vary by transaction type. Fourth, exploiting cross-asset heterogeneity in cryptocurrency-equity comovement or constructing instruments from regulatory announcements would strengthen causal identification. Fifth, incorporating high-frequency transaction data would reveal whether adaptation occurs gradually within annual windows or concentrates in discrete boom episodes. Finally, longitudinal studies tracking tokenization and central bank digital currencies will determine whether these threshold mechanisms persist as digital finance becomes embedded in traditional intermediation.

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Appendix A. Data and Diagnostics

Appendix A.1. Correlation Matrices

Table A1. Correlation matrices (Pearson ρ).

Panel A: Bank–Year Correlations						
	(1)	(2)	(3)	(4)	(5)	(6)
(1) Fee share (std.)	1.000					
(2) Loan-income growth (std., lag)	0.000	1.000				
(3) Fee share	1.000 ***	0.000	1.000			
(4) Loan-income growth (lag)	0.004	0.289 ***	0.004	1.000		
(5) Equity return	−0.014	0.008	−0.014	−0.002	1.000	
(6) Digital exposure	0.019 **	0.011	0.019 **	0.016 **	0.007	1.000
Panel B: Country–Year Correlations						
	(1)	(2)	(3)	(4)	(5)	(6)
(1) Bitcoin (BTC)	1.000					
(2) Ethereum (ETH)	0.313 ***	1.000				
(3) Ripple (XRP)	0.336 ***	0.182 ***	1.000			
(4) Binance Coin (BNB)	0.110	−0.019	−0.398 ***	1.000		
(5) Equity return	0.906 ***	0.521 ***	0.313 ***	0.402 ***	1.000	
(6) Digital exposure	0.001	0.005	0.006	0.001	0.005	1.000

Notes: Panel A computed at bank–year level (N = 18,438). Panel B was computed at the country–year level to avoid within-country duplication. *** $p < 0.01$, ** $p < 0.05$.

Appendix A.2. Variance Inflation Diagnostics

Table A2. Variance inflation factors for country–year regressors.

	Individual Coins				*Composite Index*		
	BTC	**ETH**	**XRP**	**BNB**	**Exposure**	**Equity**	**Exposure**
VIF	6.54	1.11	7.51	2.84	1.00	1.00	1.00

Notes: VIF $>$ 10 indicates multicollinearity. All returns at country–year level.

Appendix A.3. Panel Unit Root Diagnostics

Table A3. Panel unit root tests.

Variable	**Test**	**Statistic**	***p*-Value**	**Conclusion**
Cryptocurrency returns				
Bitcoin (BTC)	Fisher-ADF	22,147	<0.001	Stationary ***
Ethereum (ETH)	Fisher-ADF	23,819	<0.001	Stationary ***
Ripple (XRP)	Fisher-ADF	21,563	<0.001	Stationary ***
Binance Coin (BNB)	Fisher-ADF	24,102	<0.001	Stationary ***
Composite (equal-weighted)	Fisher-ADF	23,456	<0.001	Stationary ***
Banking outcomes				
Fee share	Fisher-ADF	19,284	<0.001	Stationary ***
Return on assets (ROA)	Fisher-ADF	18,761	<0.001	Stationary ***
Loan-income growth	Fisher-ADF	21,392	<0.001	Stationary ***
Net interest margin (NIM)	Fisher-ADF	20,145	<0.001	Stationary ***
Digital connectivity				
Internet users (% pop.)	Fisher-ADF	17,892	<0.001	Stationary ***

Notes: Fee income reflects total non-interest revenue. Fisher-type augmented Dickey–Fuller tests for panel data with 1841 banks over approximately 10 years. All variables reject the unit root null hypothesis at the 1% level. *** $p < 0.01$.

Appendix B. Heterogeneity and Robustness Checks

Appendix B.1. Digital Heterogeneity

Table A4. Coin $\times$ digital connectivity splits (fee share, SD-scaled; two-way clustered).

		High-Digital Banks			**Low-Digital Banks**		
Coin	**Digital Proxy**	β	**SE**	N	β	**SE**	N
BTC	Internet	0.193 **	0.065	1891	0.047	0.032	3668
ETH	Internet	0.221 **	0.074	1795	0.040	0.036	3212
XRP	Internet	0.200 **	0.069	1891	0.042	0.033	3668
BNB	Internet	0.248 **	0.079	1457	0.012	0.054	2227
BTC	Broadband	0.131	0.076	1891	−0.055 *	0.025	3668
ETH	Broadband	0.136	0.076	1795	−0.074 **	0.025	3212
XRP	Broadband	0.116	0.072	1891	−0.061 **	0.024	3668
BNB	Broadband	0.149 *	0.073	1457	−0.104 ***	0.026	2227

Notes: Each cell is a separate regression of standardized fee share on coin $\times$ digital with bank and year fixed effects. Standard errors clustered by bank and country–year. High/low groups defined annually by terciles of digital connectivity. ***, **, * denote significance at the 1, 5, and 10 percent levels.

Appendix B.2. Geographic Heterogeneity

Table A5. Geographic robustness: European vs. non-European banks at high connectivity.

	Europe		**Non-Europe**	
	β	**SE**	β	**SE**
Fee Share (t + 1)	0.882 *	(0.526)	−0.225	(0.724)
N (observations)	3360		790	
N (banks)	1343		161	

Notes: High-connectivity subsample only (top tercile of internet penetration, defined globally). Fee Share is standardized non-interest income as share of operating income. Crypto × Digital is the interaction of within-year standardized Bitcoin returns and internet penetration. Regressions include bank and year fixed effects. Standard errors clustered by bank. We focus on Bitcoin returns to maximize sample coverage across the full 2014–2023 period. * $p < 0.10$.

Appendix B.3. Consolidated Robustness

Table A6. Consolidated robustness checks for crypto × digital connectivity.

		Fee Share (t)		**Loan-Income Growth ($t-1$)**	
Specification	**Coin**	β	**SE**	β	**SE**
Panel A: Broadband penetration proxy					
	BTC	0.031	(0.019)	0.208	(5.073)
	EW	0.026	(0.016)	0.164	(4.762)
Panel B: Stricter winsorization (2.5–97.5 percent)					
	BTC	−0.000135	(0.000152)	0.000446 *	(0.000241)
	EW	−0.000035	(0.000036)	0.000118 **	(0.000054)
Panel C: Excluding pandemic years (2020–2021)					
	BTC	−0.000053	(0.000178)	0.000299	(0.000295)
	EW	−0.000021	(0.000041)	0.000066	(0.000065)
Panel D: Wild-bootstrap inference (p-values)					
	BTC	$p = 0.240$		$p = 0.164$	
	EW	$p = 0.186$		$p = 0.155$	

Notes: Fee income reflects total non-interest revenue. Each panel reports coefficients on (crypto return × digital connectivity) with bank and year fixed effects. Standard errors two-way clustered by bank and country–year (Panel D uses wild bootstrap with 999 replications). All variables standardized; BTC = Bitcoin; EW = equal-weighted composite return. **, * denote significance at the 1 and 5 percent levels.

Appendix B.4. Extended Outcomes (ROA, NIM)

Table A7. Extended outcome measures (ROA, NIM).

		β(ret × digital) Coefficient (SE)			
Coin	**Digital**	**ROA(t)**	**Fee Share(t)**	**Loan-Income Growth($t-1$)**	**NIM(t)**
Panel A: Broadband penetration					
BNB	Broadband	0.0377	−0.0001	0.0530	0.0000
		(0.0293)	(0.0001)	(0.0326)	(0.0000)
BTC	Broadband	0.2074	0.0000	0.2019	0.0000
		(0.1512)	(0.0007)	(0.1902)	(0.0000)
ETH	Broadband	0.0318	−0.0001	0.0376	0.0000
		(0.0235)	(0.0001)	(0.0294)	(0.0000)
XRP	Broadband	0.0082	−0.0000	0.0094	0.0000
		(0.0059)	(0.0000)	(0.0076)	(0.0000)

Table A7. *Cont.*

		β(ret × digital) Coefficient (SE)			
Coin	**Digital**	**ROA(t)**	**Fee Share(t)**	**Loan-Income Growth($t-1$)**	**NIM(t)**
Panel B: Internet penetration					
BNB	Internet	0.0514	−0.0000	−0.0073	0.0000
		(0.0245)	(0.0001)	(0.0305)	(0.0000)
BTC	Internet	0.1606	0.0004	−0.0021	−0.0000
		(0.1247)	(0.0006)	(0.1866)	(0.0000)
ETH	Internet	0.0342	0.0000	−0.0093	−0.0000
		(0.0193)	(0.0001)	(0.0278)	(0.0000)
XRP	Internet	0.0073	0.0000	−0.0002	0.0000
		(0.0048)	(0.0000)	(0.0072)	(0.0000)

Appendix B.5. Clustering Sensitivity

Table A8. Clustering sensitivity analysis.

Coin	**Outcome**	**Clustering**	**β**	**SE**
BTC	Fee share (t)	Bank-only	−0.000124	(0.000190)
		Country–year (fallback)	−0.000124	(0.000190)
		Two-way	−0.000124	(0.000155)
	Loan-income growth (t−1)	Bank-only	0.000272	(0.000315)
		Country–year (fallback)	0.000272	(0.000315)
		Two-way	0.000272	(0.000252)
EW	Fee share (t)	Bank-only	−0.000033	(0.000044)
		Country–year (fallback)	−0.000033	(0.000044)
		Two-way	−0.000033	(0.000036)
	Loan-income growth (t−1)	Bank-only	0.000077	(0.000072)
		Country–year (fallback)	0.000077	(0.000072)
		Two-way	0.000077	(0.000057)

Notes: Two-way clustering is by bank and country–year.

Appendix B.6. Reconciliation: XRP Coefficient Across Sample Definitions

Table A9. Robustness: loan growth response to XRP across alternative sample partitions.

Specification	**β**	**SE**	***p*-Value**	**N**
Pooled (full sample)	−0.0039	0.0059	0.506	17,825
Global tercile splits:				
High connectivity	−0.0167	0.0859	0.846	5811
Low connectivity	−0.0177	0.0120	0.141	5961
Global quartile splits:				
Top quartile (Q4)	−0.0181	0.0933	0.847	4371
Bottom quartile (Q1)	−0.0177	0.0127	0.164	5321
Within-year tercile splits:				
High connectivity	−0.0170	0.0177	0.336	5944
Low connectivity	−0.0150	0.0118	0.202	5943

Notes: Dependent variable is lagged, standardized loan-income growth. Models include bank and year fixed effects with two-way clustered SEs.

Appendix B.7. Linear Trend Controls

Table A10. Country-specific linear trends.

Coin	Outcome	β	SE
BTC	Fee share (t)	-1.26×10^{-4}	(0.00015)
BTC	Loan-income growth ($t-1$)	1.57×10^{-4}	(0.00025)
EW	Fee share (t)	-3.33×10^{-5}	(0.00004)
EW	Loan-income growth ($t-1$)	5.00×10^{-5}	(0.00006)

Notes: Regressions include bank and year fixed effects and country-specific linear trends.

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