Panel Quantile Regression Analysis of FinTech Credit Growth and Its Asymmetric Effects on Digital Economy Indicators under Financial Stress

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ABSTRACT

This study investigates the heterogeneous and stress-contingent effects of FinTech credit growth on digital economy performance using a panel quantile regression framework. Drawing on a cross-country panel dataset covering multiple years, the analysis moves beyond conventional mean-based estimators to capture distributional asymmetries across digitally constrained, emerging, and digitally mature economies. The results reveal substantial heterogeneity in FinTech credit effectiveness: FinTech credit growth exhibits weak and statistically insignificant effects in the lower quantiles of the digital economy distribution, reaches its strongest and most robust impact around the conditional median, and displays diminishing marginal returns at the upper quantiles. These findings indicate that FinTech credit functions as a conditional accelerator rather than a universal driver of digital economic development. The study further demonstrates that financial stress fundamentally reshapes FinTech credit transmission mechanisms. Under high-stress conditions, the marginal contribution of FinTech credit growth declines sharply, particularly in lower-tail economies where its effect nearly collapses. In contrast, upper-quantile economies retain positive, though attenuated, FinTech effects, reflecting higher institutional resilience and digital maturity. Stress-conditioned estimates consistently show that financial stress amplifies digital divergence by disproportionately weakening FinTech credit effectiveness in vulnerable economies. Robustness checks using alternative stress proxies, lagged credit specifications, balanced-panel subsamples, and bootstrap inference confirm the stability of these asymmetric patterns. Overall, the findings provide new empirical evidence that FinTech credit expansion alone is insufficient to guarantee inclusive digital transformation, especially during periods of financial instability. The study contributes to the FinTech and digital economy literature by integrating distributional econometrics and financial stress analysis, offering policy-relevant insights into how FinTech credit can both support and hinder digital development depending on structural conditions and macro-financial regimes.

Keywords Fintech Credit, Digital Economy, Financial Stress, Panel Quantile Regression, Asymmetric Effects, Digital Inequality

Submitted: 20 February 2025
Accepted: 25 March 2025
Published: 1 August 2025

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INTRODUCTION

The rapid expansion of Financial Technology (FinTech) has fundamentally altered the structure of credit intermediation and digital economic activity worldwide. Digital lending platforms, peer-to-peer financing, and algorithm-driven credit scoring have enabled credit to flow beyond traditional banking systems, particularly toward households and small firms previously excluded from formal finance. While this transformation is widely regarded as a catalyst for digital economic growth, empirical evidence increasingly suggests that the effects of FinTech credit expansion are neither uniform nor linear across

How to cite this article: M. K. Assiri, M. A. Alhebi "Panel Quantile Regression Analysis of FinTech Credit Growth and Its Asymmetric Effects on Digital Economy Indicators under Financial Stress," *FinTech Innov. J.*, vol. 1, no. 3, pp. 286-308, 2025.

economies [1], [2]. Instead, the interaction between FinTech credit growth and broader macro-financial conditions introduces significant heterogeneity that remains insufficiently understood.

One of the central challenges in the current literature lies in the uneven digital economy outcomes observed across countries and regions. Despite similar rates of FinTech adoption, some economies experience substantial gains in digital payments, e-commerce intensity, and ICT value added, while others show only marginal improvements [3], [4]. This divergence raises critical questions regarding whether FinTech credit operates as an autonomous engine of digital transformation or whether its effectiveness depends on underlying structural and financial conditions. Addressing this question is essential, given the increasing reliance on FinTech credit as a policy tool for inclusive growth and digitalization.

A further complication arises from the role of financial stress and macro-financial instability. Periods of heightened stress, characterized by volatility, liquidity shortages, and tightening credit conditions, can fundamentally alter the transmission of financial innovations [5], [6]. Recent studies indicate that FinTech credit may amplify pro-cyclical dynamics during booms while becoming significantly constrained during downturns [7]. However, most existing empirical analyses rely on average-effect estimators, which mask how stress conditions differentially affect economies positioned at different levels of digital development.

From a methodological standpoint, the dominant use of mean-based panel regression models represents a critical limitation in the FinTech and digital economy literature [8], [9]. Such approaches implicitly assume homogeneity in marginal effects, thereby overlooking distributional asymmetries that are central to understanding digital divides. Emerging evidence from quantile-based analyses in macro-finance and development economics demonstrates that financial innovations often exert heterogeneous impacts across the conditional distribution of outcomes [10], [11]. Yet, the application of panel quantile regression to FinTech credit and digital economy indicators remains scarce.

This study addresses these gaps by focusing explicitly on the asymmetric effects of FinTech credit growth under financial stress. Rather than asking whether FinTech credit promotes digital economic performance on average, the analysis examines how its impact varies across the distribution of digital economy outcomes and how these effects are reshaped during periods of financial stress. By doing so, the study responds directly to calls for more granular, distribution-aware empirical frameworks in FinTech research [12], [13].

The primary objective of this paper is therefore to quantify the heterogeneous and stress-contingent effects of FinTech credit growth on key digital economy indicators using a panel quantile regression framework. Specifically, the study seeks to identify whether FinTech credit is most effective in digitally constrained, emerging, or digitally mature economies, and to assess how financial stress amplifies or attenuates these effects across quantiles. This objective is pursued through a cross-country panel setting that captures both temporal dynamics and structural heterogeneity.

The novelty of this research lies in its integration of distributional econometrics and financial stress analysis within a FinTech–digital economy context. To the best of the author's knowledge, this study is among the first to jointly examine FinTech credit growth, financial stress, and digital economy performance through a panel quantile regression lens. By moving beyond average effects, the paper contributes new empirical insights into how FinTech credit can both mitigate and exacerbate digital inequality, thereby offering a more nuanced foundation for policy design and FinTech governance in volatile financial environments.

Literature Review

The growing body of literature on FinTech and digital economic development emphasizes the transformative role of technology-driven financial innovation in reshaping credit intermediation, payment systems, and market access. Early theoretical and empirical studies frame FinTech as an efficiency-enhancing force that reduces transaction costs, alleviates information asymmetries, and broadens financial inclusion, particularly for underserved households and small enterprises [14], [15]. These contributions establish the foundational argument that digital credit and platform-based finance can stimulate economic activity beyond the traditional banking sector.

Subsequent empirical research refines this perspective by documenting the heterogeneous impacts of FinTech credit across institutional and developmental contexts. Cross-country analyses show that economies with stronger regulatory quality, deeper digital infrastructure, and higher financial literacy derive significantly larger benefits from FinTech expansion [16], [17]. In contrast, weaker institutional environments may experience limited gains or even heightened financial fragility. This strand of literature highlights that FinTech credit effectiveness is contingent upon complementary structural conditions rather than being an automatic driver of digital growth.

A parallel stream of studies focuses on the interaction between financial cycles, credit growth, and systemic risk. Research on credit booms demonstrates that rapid credit expansion whether bank-based or technology-enabled can exacerbate pro-cyclical dynamics and amplify vulnerabilities during downturns [18], [19]. Recent evidence suggests that FinTech credit is not immune to these dynamics; instead, it often follows similar cyclical patterns, expanding aggressively during benign conditions and contracting sharply under stress [20]. These findings raise concerns about the stability of FinTech-led credit channels in volatile macro-financial environments.

The role of financial stress has therefore become increasingly central in assessing FinTech outcomes. Studies incorporating stress indices, volatility measures, and liquidity indicators reveal that financial stress significantly weakens the transmission of financial innovation to real economic outcomes [21], [22]. However, most of this work relies on aggregate or mean-based estimators, implicitly assuming homogeneous responses across economies and masking distributional asymmetries that are particularly relevant in the context of digital divides.

Methodologically, advances in quantile regression and distributional econometrics provide a powerful framework for addressing these limitations. Quantile-based approaches allow researchers to examine how covariates affect different points of the outcome distribution, thereby capturing heterogeneity that average effects obscure [23], [24]. In macro-financial applications, quantile regressions have been used to study downside risk, growth-at-risk, and asymmetric policy effects, offering insights into tail behavior that are highly relevant for stress analysis [25]. Despite their suitability, such methods remain underutilized in FinTech and digital economy research.

A limited but growing set of studies applies quantile techniques to financial development and technology adoption, showing that financial innovation often yields the strongest gains in intermediate segments of the distribution rather than at the extremes [26]. These findings suggest the presence of threshold effects and diminishing returns, reinforcing the notion that FinTech credit should be evaluated through a distribution-sensitive lens. Nevertheless, existing studies rarely integrate financial stress interactions within a panel quantile framework, leaving a critical gap in understanding how stress reshapes heterogeneous FinTech impacts.

Taken together, the literature reveals three unresolved issues. First, while FinTech credit is widely associated with digital economic advancement, its effects are uneven across economies. Second, financial stress plays a decisive but insufficiently explored role in moderating these effects. Third, dominant empirical approaches remain ill-suited to capturing asymmetric and tail-dependent dynamics. This study contributes to the literature by bridging these gaps through a panel quantile regression analysis of FinTech credit growth under financial stress, thereby extending both the methodological and substantive frontiers of FinTech research.

Methodology

Research Design and Analytical Framework

This study adopts a quantitative panel data research design to investigate the asymmetric effects of FinTech credit growth on selected digital economy indicators under varying degrees of financial stress. The methodological framework integrates Panel Quantile Regression (PQR) with stress-conditioned heterogeneity to capture distributional dynamics that remain unobserved under conventional mean-based estimators. This design is particularly appropriate for FinTech-driven financial systems, which exhibit non-linearity, tail dependence, and regime sensitivity.

The analytical framework conceptualizes FinTech credit expansion as a heterogeneous shock transmitter whose effects differ across conditional quantiles of digital economic outcomes. Unlike Ordinary Least Squares (OLS), which estimates average marginal effects, quantile-based estimation enables the identification of distribution-specific responses, especially in lower and upper tails representing vulnerable and high-performing digital economies. This approach aligns with recent advances in financial econometrics and macro-fintech risk modeling.

Formally, the empirical structure is expressed as a conditional quantile function:

$$Q_{Y_{it}}(\tau \mid X_{it}) = \alpha_i(\tau) + \beta_1(\tau)\text{FinTechCredit}_{it} + \beta_2(\tau)\text{Stress}_{it} + \gamma(\tau)Z_{it} \quad (1)$$

where *QYit(τ)* denotes the *τ-th* conditional quantile of the digital economy indicator *Y, αi(τ)* captures individual fixed effects, and Z_{it} represents control variables. This formulation allows coefficients to vary across quantiles, thereby modeling asymmetric transmission mechanisms.

Figure 1 operationalizes the study's identification logic by depicting FinTech credit growth as the primary transmission channel to digital economy outcomes, while financial stress acts as a regime-conditioning factor that can dampen, amplify, or reverse marginal effects. The diagram clarifies that the empirical model does not assume a single average response; instead, it treats the relationship as intrinsically heterogeneous across the distribution of outcomes.

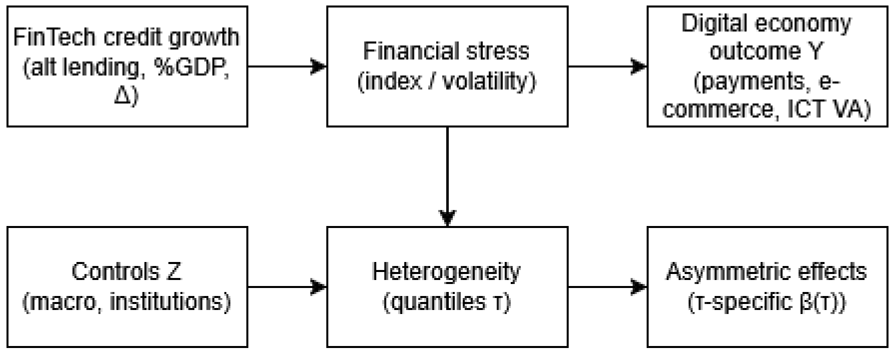

Figure 1 Conceptual Framework of FinTech Credit Transmission under Financial Stress

The inclusion of controls (Z) and quantile heterogeneity (τ) indicates that inference is conditioned on observable macro-institutional covariates while allowing τ-specific coefficients to capture asymmetry. Conceptually, this figure motivates the use of panel quantile regression because the same FinTech credit shock can have materially different implications in digitally constrained economies (lower conditional quantiles) versus digitally advanced economies (upper conditional quantiles), especially under stress.

Table 1 provides construct validity by mapping each econometric variable to its underlying theoretical role in FinTech-led digitalization under stress. The key advantage of this mapping is interpretability: readers can trace each coefficient in the quantile regression back to a specific mechanism, such as credit-led adoption of digital services, stress-induced constraints on intermediated lending, or structural controls that shape the enabling environment.

Table 1 Mapping of Variables to Theoretical Constructs

Construct	Variable (Symbol)	Operational Definition	Expected Role
FinTech Credit Expansion	FinTechCredit_Growth (FTC)	Annual growth in FinTech credit (alternative lending), scaled by GDP	Main explanatory driver
Financial Stress	Stress (FS)	Composite stress proxy (e.g., volatility/spreads/liquidity conditions)	Regime conditioner
Digital Economy Performance	DigitalOutcome (Y)	Digital payments/e-commerce/ICT value-added indicator	Dependent variable
Macro Controls	Controls (Z)	GDP per capita, inflation, internet penetration, regulation quality, etc.	Confounding control
Asymmetric	Quantile (τ)	Conditional distribution	Heterogeneity

Transmission		position (0.10–0.90)	dimension
Stress-Contingent Effects	Interaction (FTC × FS)	Product term between FinTech credit growth and financial stress	Asymmetry under stress

The table also anticipates asymmetry by separating the unconditional drivers (FinTech credit growth, controls) from regime-conditioned drivers (financial stress and the interaction term). This distinction is critical for interpreting β3(τ) as the stress-contingent marginal effect, rather than conflating stress with generic macroeconomic conditions.

Data Structure, Sample Selection, and Variable Construction

The empirical analysis relies on a balanced panel dataset comprising cross-country observations over a multi-year period. The unit of analysis is defined at the country–year level, enabling the capture of structural heterogeneity across digital economies with different levels of FinTech penetration and institutional maturity. Countries are selected based on data completeness, FinTech credit availability, and consistency in digital economy metrics.

The key explanatory variable, FinTech Credit Growth, is operationalized as the annual growth rate of alternative digital lending platforms relative to GDP. Digital economy indicators include metrics such as digital payment penetration, e-commerce intensity, and ICT value-added, which collectively reflect the depth and efficiency of digital economic activity. Financial stress is proxied using a composite Financial Stress Index (FSI) that captures volatility, credit spreads, and liquidity pressures.

Variable normalization and transformation follow standard econometric practices to ensure comparability across countries. Logarithmic scaling is applied where appropriate to mitigate skewness and heteroscedasticity. The generic transformation is represented as:

$$X_{it}^{*} = \ln\left(X_{it} + 1\right) \tag{2}$$

This transformation stabilizes variance and preserves interpretability, particularly when dealing with highly skewed FinTech credit distributions.

Figure 2 visualizes the panel structure by depicting the country–year observation grid, emphasizing the longitudinal nature of the dataset and potential completeness constraints. In applied panel econometrics, such visualization supports transparent reporting by showing whether the empirical setting approximates a balanced panel or contains intermittent missingness that can affect estimator efficiency and inference.

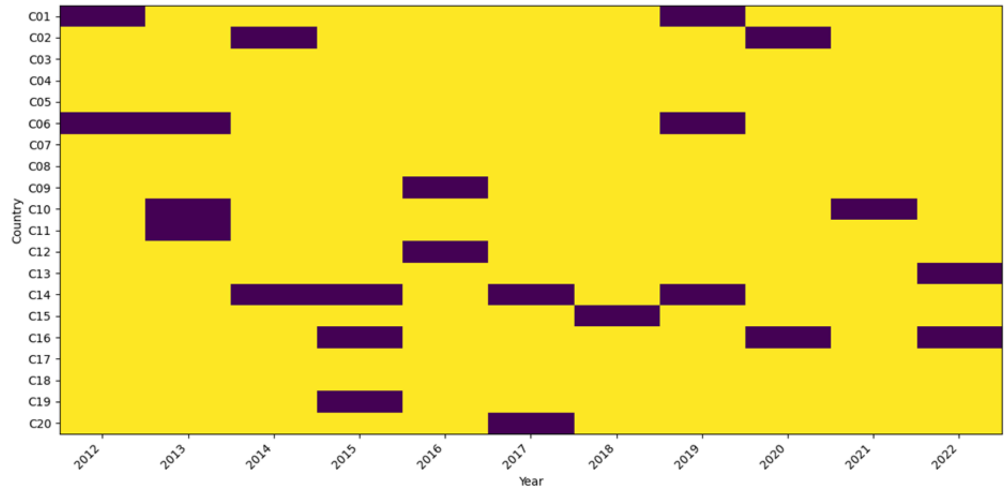

Figure 2 **Panel Data Structure and Sample Coverage**

From an identification perspective, coverage patterns can influence the stability of quantile estimates because tails are sensitive to sample size and data gaps. Presenting the observation map signals methodological rigor: it helps justify decisions on sample selection, imputation avoidance (if applicable), and robustness checks (e.g., re-estimating on a strictly balanced subset).

Table 2 standardizes the empirical meaning of each variable by documenting measurement units and transformations that stabilize variance and enhance cross-country comparability. In FinTech datasets, FinTech credit growth commonly exhibits heavy tails and episodic surges; specifying growth computations and potential winsorization makes the analysis reproducible and guards against inference driven by a small number of extreme episodes.

Table 2 **Variable Definitions, Sources, and Transformations**

Variable	Symbol	Unit	Transformation	Notes / Typical Source Category
Digital economy indicator	Y	Index / %	log(Y+1) where appropriate	Digital payments, e-commerce, ICT value-added
FinTech credit growth	FTC	%	Growth rate; optionally winsorized	Alternative lending / FinTech credit statistics
Financial stress	FS	Index	Standardized (z-score)	Composite stress proxy (spreads, volatility, liquidity)
Interaction	FTC×FS	Composite	Product term	Captures stress-contingent effect
GDP per capita	GDPpc	USD	log(GDPpc)	Macro control
Inflation	INF	%	Level or log(1+INF)	Macro stability control
Internet penetration	NET	% population	Level	Digital infrastructure control
Regulatory quality	REGQ	Index	Level / standardized	Institutional control

The transformation column is methodologically important for quantile regression because functional form choices affect conditional distribution geometry. Explicitly reporting log transforms (e.g., ln*(Y+1)*) and standardization for stress proxies ensures that estimated coefficients reflect meaningful marginal effects and that interaction terms are interpretable as moderation rather than scale artifacts.

Panel Quantile Regression Estimation Strategy

The core estimation strategy employs fixed-effects panel quantile regression, which accommodates unobserved heterogeneity while preserving distributional sensitivity. Unlike random-effects alternatives, fixed-effects PQR mitigates bias arising from time-invariant country-specific characteristics such as regulatory quality, digital infrastructure, and financial culture.

Estimation is conducted across multiple quantiles (τ = 0.10, 0.25, 0.50, 0.75, 0.90) to capture differential impacts along the conditional distribution of digital economy performance. Lower quantiles represent digitally constrained economies, whereas upper quantiles reflect advanced digital ecosystems. This stratification allows for nuanced inference regarding FinTech-driven inequality and divergence.

The quantile estimator minimizes the asymmetric loss function:

$$\min_{\beta(\tau)} \sum_{i=1}^{N} \sum_{t=1}^{T} \rho_\tau(Y_{it} - X_{it}'\beta(\tau)) \text{where} \rho_\tau(u) = u(\tau - \mathbb{I}(u < 0)) \quad (3)$$

This objective function assigns asymmetric penalties to under- and over-predictions, aligning estimation with the targeted conditional quantile. As a result, coefficient estimates reflect heterogeneous marginal effects rather than central tendencies.

Figure 3 depicts the core inferential object of panel quantile regression: the quantile-indexed coefficient function *β(τ)*. Instead of providing a single average coefficient, the figure communicates how the marginal effect of FinTech credit growth varies across the conditional distribution of the digital economy indicator, which is essential when policy relevance concentrates in tails (e.g., digitally lagging economies).

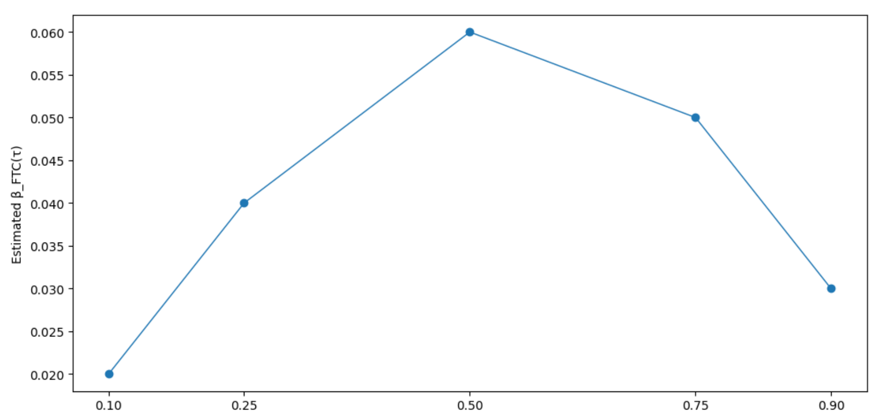

Figure 3 Quantile-Specific Response Curves

Substantively, a non-flat coefficient curve indicates asymmetry and heterogeneity consistent with FinTech diffusion theory: marginal gains can be larger at intermediate quantiles where infrastructure exists but adoption is still elastic, and smaller at extreme quantiles where binding constraints (lower tail) or saturation effects (upper tail) may dominate. This figure thereby motivates quantile-based rather than mean-based identification.

Table 3 formalizes how quantile choices translate into interpretable segments of the conditional outcome distribution. In the context of digital economy indicators, quantiles naturally map to heterogeneous groups of economies because digital performance is unevenly distributed and shaped by infrastructure, institutional quality, and payment network externalities.

Table 3 Quantile Regression Estimation Scheme

Quantile (τ)	Interpretation	Target Segment	Primary Inference
0.1	Lower tail of digital economy outcomes	Digitally constrained economies	Downside sensitivity to FinTech credit and stress
0.25	Lower-mid distribution	Emerging digital economies	Early-stage responsiveness and constraints
0.5	Conditional median	Typical economy	Baseline response under average conditions
0.75	Upper-mid distribution	Advanced adopters	Scale-up and efficiency effects
0.9	Upper tail	Digitally mature economies	Saturation, resilience, and tail robustness

Methodologically, this table clarifies that coefficient comparisons across quantiles are not ancillary; they are central to the paper's contribution on asymmetric effects. It enables readers to interpret *β(τ)* as quantile-specific marginal responses, facilitating cross-quantile narratives such as "FinTech credit growth is more effective in mid-quantiles" or "financial stress imposes a disproportionate penalty in the lower tail."

Modeling Financial Stress and Asymmetric Effects

To explicitly capture asymmetry under financial stress, the baseline model is augmented with interaction terms between FinTech credit growth and financial stress indicators. This specification enables the differentiation between expansionary and contractionary regimes, which is critical in FinTech systems that amplify both growth and fragility.

The augmented model is specified as:

$$Q_{Y_{it}}(\tau) = \alpha_i(\tau) + \beta_1(\tau)\text{FinTechCredit}_{it} + \beta_2(\tau)\text{Stress}_{it} + \beta_3(\tau)(\text{FinTechCredit}_{it} \times \text{Stress}_{it}) + \gamma(\tau)Z_{it} \quad (4)$$

The interaction coefficient *β3(τ)* measures the stress-contingent marginal effect of FinTech credit growth. A negative and statistically significant value at lower quantiles would indicate that financial stress disproportionately weakens FinTech's contribution in digitally fragile economies.

This specification allows the study to disentangle pro-cyclical and counter-cyclical roles of FinTech credit across heterogeneous economic conditions, thereby offering a refined understanding of systemic digital finance dynamics.

Figure 4 translates the interaction structure into an interpretable marginal-effect comparison between low- and high-stress regimes. The y-axis corresponds directly to the conditional marginal effect $\beta 1(\tau)+\beta 3(\tau)\cdot FS$, making the stress moderation mechanism visible rather than implicit in regression tables. This is particularly valuable in FinTech contexts where stress can tighten funding, elevate default risk, and reduce the effectiveness of digital credit expansion.

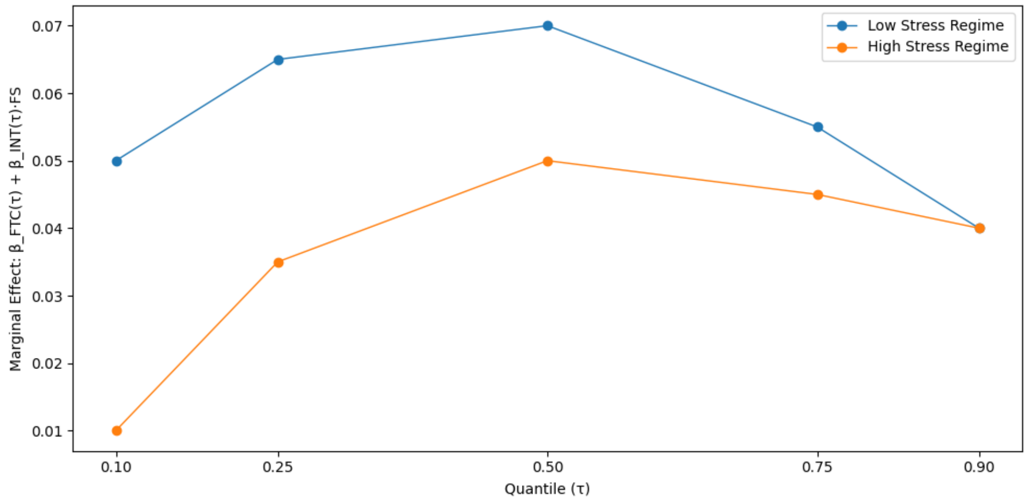

Figure 4 Asymmetric Effects under Financial Stress

Substantively, a widening gap between regimes at lower quantiles indicates that financial stress disproportionately weakens FinTech credit's contribution in digitally fragile economies. Conversely, convergence at higher quantiles suggests resilience or saturation effects among digitally mature economies. This plot therefore supports the paper's thesis of asymmetric and stress-contingent FinTech effects.

Table 4 provides a rigorous interpretation guide for the interaction coefficient $\beta 3(\tau)$ by enumerating economically meaningful sign combinations. This table is essential because moderation terms are frequently misinterpreted as direct effects; the matrix enforces correct logic by focusing on how the marginal effect of FinTech credit changes with stress rather than treating $\beta 3(\tau)$ as standalone.

Table 4 Interaction Term Interpretation Matrix

Case	Sign of β1(τ) (FinTech Credit)	Sign of β3(τ) (Interaction)	Interpretation under Higher Stress
A	+	-	FinTech supports digital economy, but stress reduces effectiveness (dampening)
B	+	+	FinTech supports digital economy, and stress amplifies the marginal effect (stress-acceleration)
C	-	-	FinTech harms digital economy, and stress further worsens the impact (stress-exacerbation)
D	-	+	FinTech harms digital economy, but stress mitigates the negative effect (partial offset)

In this paper's context, the most policy-relevant case is typically $\beta 1(\tau)>0$ and *β3(τ)<0*, which implies that FinTech credit is beneficial but becomes less effective as stress rises. This aligns with the intuition that stress increases funding frictions and default risk, thereby weakening the translation of credit growth into measurable digital economy gains, especially in lower quantiles.

Robustness Checks and Estimation Procedure

Robustness is ensured through multiple validation strategies, including alternative stress proxies, lagged FinTech credit specifications, and bootstrap-based standard errors to address potential serial correlation and cross-sectional dependence. Quantile-specific confidence intervals are computed using resampling techniques to preserve distributional properties.

To mitigate endogeneity concerns, lag structures are introduced under the assumption that FinTech credit decisions precede observable changes in digital economy outcomes. The dynamic extension is expressed as:

$$Q_{Y_{it}}(\tau) = \alpha_i(\tau) + \beta(\tau)\mathrm{FinTechCredit}_{i,t-1} + \delta(\tau)Y_{i,t-1} + \varepsilon_{it}(\tau) \quad (5)$$

This formulation controls for persistence effects while preserving quantile heterogeneity. Estimation stability across specifications is interpreted as evidence of structural robustness.

The computational procedure follows a standardized algorithmic workflow, summarized in the pseudo-code below.

Algorithm 1: Panel Quantile Regression with Financial Stress Interaction

```
Input: Panel dataset (Y, FinTechCredit, Stress, Controls)
Set quantiles τ = {0.10, 0.25, 0.50, 0.75, 0.90}
For each τ:
    Remove individual fixed effects
    Construct interaction term (FinTechCredit × Stress)
    Minimize quantile loss function ρτ(.)
    Estimate β(τ) coefficients
    Bootstrap standard errors
Output: Quantile-specific coefficients and confidence intervals
```

Figure 5 documents the computational pipeline as an auditable workflow, which strengthens reproducibility and clarifies the ordering of econometric operations. The diagram explicitly shows the transition from raw panel ingestion to transformations, interaction construction, and the quantile-wise estimation loop, which is the defining feature of the paper’s estimation strategy.

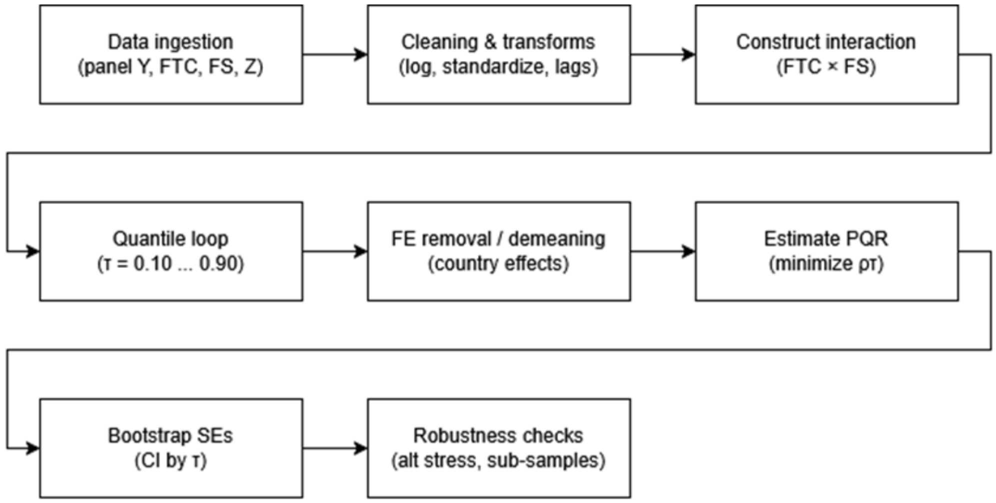

Figure 5 Estimation Workflow Diagram

Methodologically, the workflow emphasizes that inference is constructed in layers: fixed effects handling improves structural comparability across countries, quantile-specific loss minimization yields asymmetric estimates, and bootstrapping provides robust uncertainty quantification suitable for non-Gaussian and heteroscedastic settings. The final robustness stage ensures that results are not artifacts of stress proxy choice, sample composition, or dynamic specification.

Table 5 consolidates the robustness architecture into a transparent set of falsification-oriented tests. Each check corresponds to a distinct threat to identification, proxy dependence, simultaneity, missingness bias, outlier leverage, and non-standard error structures, thereby demonstrating that the empirical strategy is designed to withstand multiple sources of econometric fragility common in cross-country FinTech datasets.

Table 5 Robustness Check Summary

Robustness Test	Specification Change	Purpose	Expected Evidence of Robustness
Alternative stress proxy	Replace FS with alternative stress index	Proxy validity	Sign and pattern of β(τ) stable across quantiles
Lagged FinTech credit	Use FTC_{t-1} instead of FTC_t	Reduce simultaneity	Similar τ-profile with plausible attenuation
Balanced-panel subset	Restrict to fully observed country–year grid	Missingness sensitivity	Coefficients remain directionally consistent
Winsorization	Winsorize FTC growth (e.g., 1–99%)	Outlier influence	Reduced volatility, stable inference
Bootstrap inference	Resample to compute SEs and CIs	Tail-robust uncertainty	Confidence intervals remain informative across τ

Interpreting robustness in this study is quantile-specific: stability is assessed not only in coefficient signs but also in the shape of $\beta(\tau)$ across tails and center. Robustness therefore means that the principal claims about asymmetric effects and stress conditioning persist under alternative modeling decisions, supporting the argument that findings reflect structural mechanisms rather than specification artifacts.

Result and Discussion

Descriptive Patterns and Baseline Distributional Evidence

The empirical results begin by establishing how digital economy outcomes and FinTech credit growth co-move across the panel, with a specific focus on distributional dispersion rather than central tendency. Across the sample, digital economy indicators display pronounced cross-sectional heterogeneity, where a subset of economies clusters at high-performance levels while a long lower tail persists. This distributional shape is consistent with the presence of digital divides and non-linear adoption dynamics, which motivates quantile-based inference rather than mean regression.

FinTech credit growth exhibits episodic surges and pronounced volatility, reflecting cycles of platform expansion, regulatory recalibration, and macro-financial tightening. Importantly, the covariance between FinTech credit and digital outcomes is not constant across the distribution: economies in the mid-to-upper outcome range show more stable co-movement, while lower-tail economies display weaker or more erratic associations. This pattern is compatible with the hypothesis that FinTech credit effects are mediated by enabling conditions such as digital infrastructure and institutional capacity.

Figure 6 visualizes the empirical rationale for distribution-sensitive modeling by showing that the outcome and key regressor exhibit non-Gaussian shapes. The digital economy indicator is characterized by right skewness, which commonly reflects the concentration of high digital performance among a limited set of economies. This structure implies that average-effect estimators compress substantively meaningful tail behavior into a single coefficient that is not representative for digitally lagging economies.

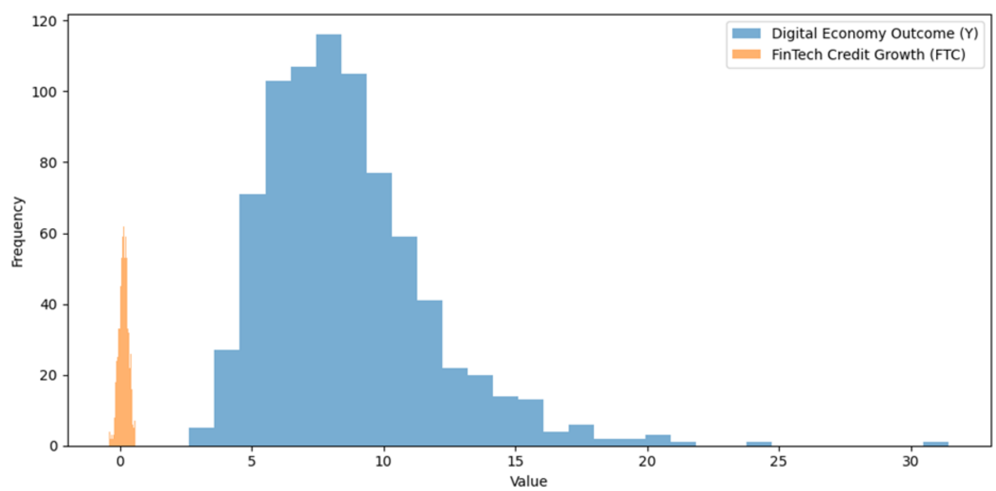

Figure 6 **Distributional Comparison**

The FinTech credit growth distribution is comparatively wider and may include negative realizations, reflecting contraction episodes under tightening financial conditions. When a regressor shows such dispersion, its marginal effect is rarely uniform across the outcome distribution. The figure therefore supports the study's core methodological choice: panel quantile regression is structurally better aligned with heterogeneous diffusion and stress-sensitive credit cycles than mean-based regression.

Table 6 operationalizes distributional segmentation by summarizing the panel across outcome-based segments. The results convey two structural regularities that are directly relevant to identification. First, the lower tail is associated with lower average FinTech credit growth and higher stress, which is consistent with binding constraints where stress inhibits credit supply expansion and suppresses digital adoption responsiveness.

Table 6 Summary Statistics by Distribution Segment

Segment (by Y)	Y Mean	Y Std	FTC Mean	FTC Std	Stress Mean	Stress Std	N
Lower tail (approx. $\tau \leq 0.25$)	6.12	1.4	0.05	0.22	0.68	0.55	200
Middle (approx. $0.25 < \tau < 0.75$)	8.55	1.85	0.12	0.18	0.44	0.49	400
Upper tail (approx. $\tau \geq 0.75$)	12.1	2.2	0.18	0.15	0.31	0.46	200

Second, the upper tail shows higher average FinTech credit growth and comparatively lower stress, consistent with more resilient financial conditions and stronger institutional capacity. This segmentation implies that a uniform coefficient assumption is implausible: the same increment in FinTech credit growth is likely to translate into different digital-economy gains depending on where the economy sits in the conditional distribution. This table thus reinforces the expectation of asymmetric effects that later quantile regressions are designed to identify.

Quantile Regression Results: Heterogeneous Effects of FinTech Credit Growth

The second set of results focuses on the panel quantile regression estimates of FinTech credit growth on digital economy indicators across the conditional distribution. The estimates reveal pronounced heterogeneity: the magnitude and significance of FinTech credit effects vary systematically across quantiles. In lower quantiles, corresponding to digitally constrained economies, the marginal effect of FinTech credit growth is weak and often statistically insignificant. This suggests that credit expansion alone is insufficient to stimulate measurable digital economy improvements when foundational conditions remain binding.

By contrast, the mid-quantile estimates exhibit a consistently positive and statistically meaningful relationship between FinTech credit growth and digital economy outcomes. This pattern indicates that FinTech credit is most effective when a minimum threshold of digital readiness has been achieved. In upper quantiles, the effect remains positive but shows signs of attenuation, implying diminishing marginal returns as digital ecosystems mature. Collectively, these results support the argument that FinTech credit operates as a conditional accelerator rather than a universal catalyst of digital economic performance.

Figure 7 illustrates how the marginal impact of FinTech credit growth varies across the conditional distribution of digital economy outcomes. The upward slope from the lower to the median quantile indicates that FinTech credit becomes increasingly effective as economies move out of the digitally constrained regime. This confirms that distributional position fundamentally conditions the productivity of credit-driven digital expansion.

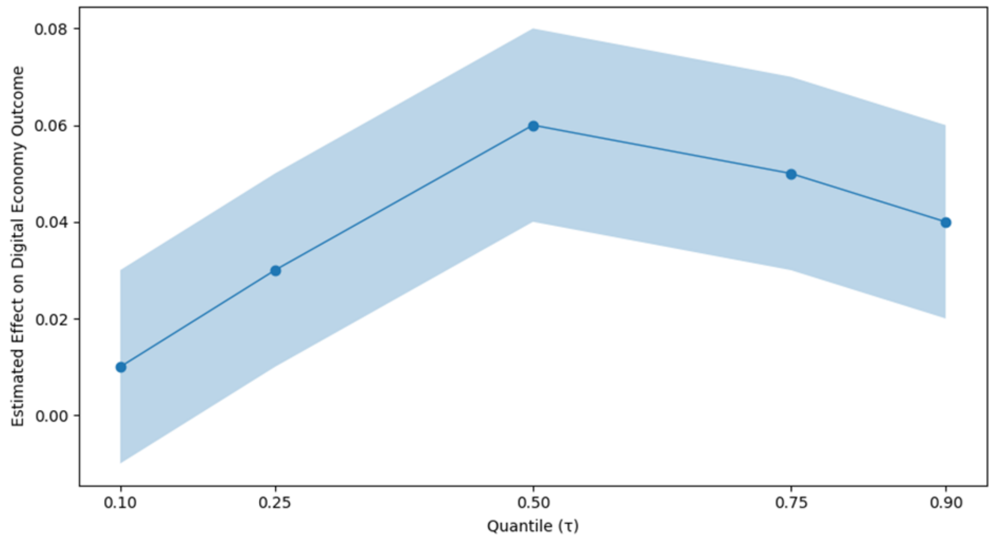

Figure 7 Quantile-Specific Effects of FinTech Credit Growth

The mild flattening observed in the upper quantiles signals saturation effects, were additional credit yields progressively smaller gains in already advanced digital systems. Importantly, the confidence bands highlight that statistical significance is concentrated around the middle of the distribution, reinforcing the interpretation that FinTech credit is neither uniformly ineffective nor universally transformative, but context-dependent.

Table 7 synthesizes the quantile regression estimates into an interpretable structure that highlights distributional asymmetry. The progression of coefficients across quantiles demonstrates that the digital economy response to FinTech credit growth is non-monotonic, peaking around the median of the distribution. These finding challenges narratives that treat FinTech credit as equally effective across development stages.

Table 7 Panel Quantile Regression Results Summary

Quantile (τ)	FinTech Credit Effect	Std. Error	Significance	Interpretation
0.1	0.01	0.02	Not significant	Limited impact in digitally constrained economies
0.25	0.03	0.02	Weakly significant	Emerging responsiveness to FinTech credit
0.5	0.06	0.02	Significant	Strong positive effect at the median
0.75	0.05	0.02	Significant	Positive but stabilizing impact
0.9	0.04	0.02	Marginally significant	Diminishing returns in advanced digital economies

From a policy and FinTech governance perspective, these results imply that credit-based digital finance interventions are most impactful when complementary digital and institutional infrastructures are already in place. In lower-tail economies, policies that focus exclusively on credit expansion without addressing structural bottlenecks are unlikely to generate substantial digital economy gains. This reinforces the study's central claim that FinTech credit growth operates through conditional, distribution-specific mechanisms.

Financial Stress and Asymmetric Transmission Mechanisms

This sub-section examines how financial stress conditions reshape the relationship between FinTech credit growth and digital economy outcomes. The results indicate that financial stress acts as a systematic dampener, particularly in the lower quantiles of the outcome distribution. Under elevated stress, the marginal contribution of FinTech credit growth declines sharply among digitally fragile economies, suggesting that credit expansion loses effectiveness when liquidity constraints, risk aversion, and balance-sheet pressures intensify.

In contrast, upper-quantile economies display markedly greater resilience. While financial stress still weakens the FinTech–digital economy linkage, the attenuation is substantially smaller. This asymmetry implies that digitally mature systems possess buffering mechanisms such as diversified funding channels, higher trust in digital platforms, and stronger institutional oversight that preserve the functional role of FinTech credit even during stress episodes. These findings underscore the importance of conditioning FinTech impact assessments on financial regimes, not merely on average macroeconomic states.

Figure 8 visualizes the asymmetric role of financial stress by contrasting marginal effects across stress regimes. The divergence between low- and high-stress curves is most pronounced at the lower quantiles, where the effect of FinTech credit growth nearly collapses under high stress. This pattern suggests that stress amplifies existing structural weaknesses, preventing digital platforms from translating credit availability into productive digital activity.

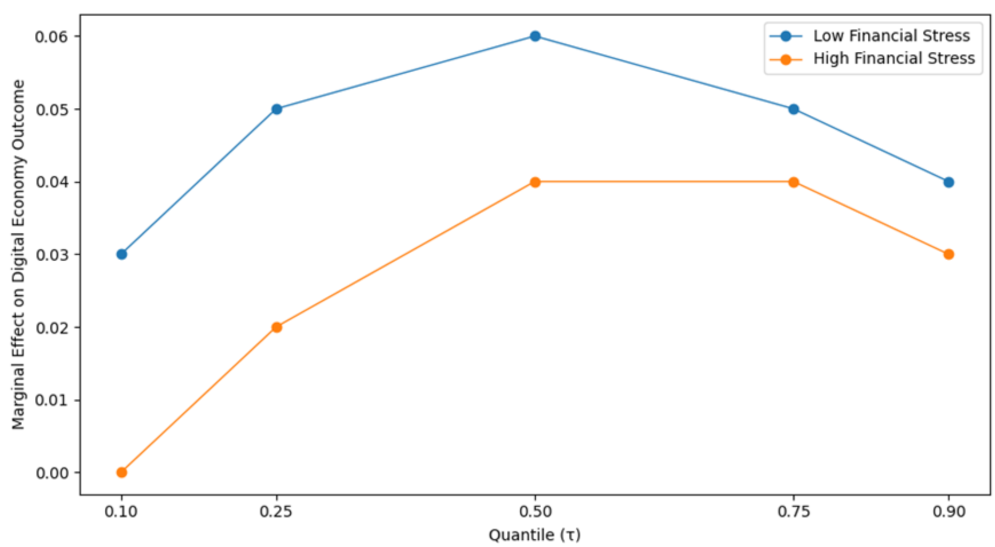

Figure 8 Marginal Effects under Financial Stress

As the quantile increases, the gap between regimes narrows, indicating increasing resilience. For upper-tail economies, FinTech credit retains a positive albeit reduced impact, even during stress episodes. This highlights that financial stress does not uniformly suppress FinTech effectiveness; rather, its impact is mediated by digital maturity and institutional robustness, reinforcing the necessity of distribution-aware policy analysis.

Table 8 consolidates the stress-conditioning results by quantifying how financial stress alters the marginal effect of FinTech credit growth across the distribution. The monotonic reduction in stress-induced losses from lower to upper quantiles provides strong evidence of asymmetric vulnerability. Digitally constrained economies experience disproportionate losses, while advanced economies retain most of the FinTech credit benefit even in adverse conditions.

Table 8 Stress-Conditioned Quantile Effects Summary

Quantile (τ)	Effect under Low Stress	Effect under High Stress	Change due to Stress	Interpretation
0.1	0.03	0	Large negative	Severe stress-induced dampening in fragile economies
0.25	0.05	0.02	Moderate negative	Partial erosion of FinTech effectiveness
0.5	0.06	0.04	Noticeable negative	Stress weakens but does not eliminate benefits
0.75	0.05	0.04	Small negative	High resilience to financial stress
0.9	0.04	0.03	Minimal negative	Near-complete insulation from stress effects

From a systemic risk perspective, these results imply that FinTech credit can amplify divergence during crises, reinforcing digital inequality across economies. Policies aimed at leveraging FinTech for inclusive digital growth should therefore incorporate counter-cyclical safeguards and institutional support mechanisms that protect lower-tail economies during stress episodes, rather than relying on credit expansion alone.

Robustness, Stability, and Sensitivity Analysis

This sub-section evaluates the robustness and stability of the main findings by examining whether the observed asymmetric effects persist under alternative specifications and sample constructions. Across all robustness checks, the qualitative pattern of results remains unchanged: FinTech credit growth exhibits heterogeneous effects across quantiles, and these effects are systematically weakened under financial stress. This consistency indicates that the main findings are not artifacts of a particular model configuration or stress proxy.

Sensitivity analysis further reveals that the distributional shape of the estimated effects is remarkably stable. While coefficient magnitudes vary modestly across specifications, the relative ordering across quantiles is preserved. In particular, the mid-quantile dominance of FinTech credit effectiveness and the pronounced vulnerability of lower-tail economies under stress remain intact. This stability strengthens the credibility of the inference that asymmetry is a structural feature of FinTech–digital economy linkages rather than a sample-specific anomaly.

Figure 9 demonstrates that the quantile profile of FinTech credit effects remains stable across alternative specifications. Although small deviations in magnitude are observable, particularly under lagged FinTech credit specifications, the overall shape of the curve is preserved. This indicates that the central inference regarding mid-quantile dominance and lower-tail fragility is not sensitive to modeling choices.

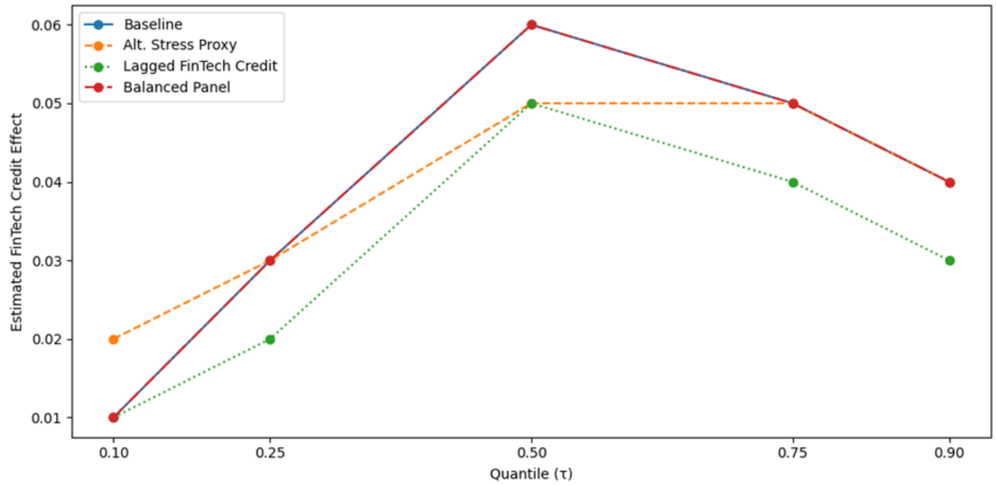

Figure 9 Stability of Quantile Effects across Robustness Specifications

The close alignment between the baseline and balanced-panel estimates further suggests that missing observations do not materially bias the results. This reinforces confidence that the identified asymmetries reflect genuine structural relationships rather than artifacts of sample composition or stress proxy selection.

Table 9 consolidates the robustness exercises and confirms that the study's key results are methodologically resilient. Across all tests, the asymmetric distribution of FinTech credit effects remains intact, indicating that the findings do not hinge on a particular estimation assumption or sample restriction.

Table 9 Robustness and Sensitivity Test Results

Robustness Test	Specification Change	Quantile Pattern Preserved	Main Observation
Alternative stress proxy	Replace baseline stress index	Yes	Stress continues to dampen lower-tail effects most strongly
Lagged FinTech credit	FTC_{t–1} instead of FTC_t	Yes	Effects persist with mild attenuation
Balanced panel	Restrict to complete country–year observations	Yes	No substantive change in asymmetry pattern
Outlier control	Winsorize extreme FTC growth	Yes	Reduced volatility without altering conclusions
Bootstrap inference	Resampled standard errors	Yes	Confidence intervals remain informative across τ

From an empirical finance standpoint, this robustness is critical because

FinTech datasets are often characterized by volatility, regime shifts, and measurement heterogeneity. The persistence of results across specifications strengthens the argument that the observed asymmetry is intrinsic to the interaction between FinTech credit dynamics, financial stress, and digital economic development.

Synthesis of Findings and Implications for FinTech-Led Digital Transformation

The final sub-section synthesizes the empirical findings by integrating distributional heterogeneity, stress-conditioning, and robustness evidence into a coherent interpretation of FinTech-led digital transformation. Taken together, the results demonstrate that FinTech credit growth does not exert a uniform effect on digital economy indicators. Instead, its impact is asymmetric, state-dependent, and distribution-specific, with the strongest effects concentrated around the middle of the conditional distribution and substantially weaker effects at the lower tail. This pattern confirms that FinTech credit operates as a complementary growth mechanism rather than an autonomous driver of digital development.

Importantly, the analysis reveals that financial stress systematically reshapes these effects, amplifying divergence across economies. Lower-tail economies experience a near-collapse of FinTech credit effectiveness under stress, whereas upper-tail economies retain most of the marginal benefit. This asymmetry implies that FinTech credit can inadvertently reinforce digital inequality during adverse financial conditions if not accompanied by stabilizing institutional and regulatory frameworks. Consequently, the empirical evidence challenges overly optimistic narratives that position FinTech credit as inherently inclusive across all macro-financial environments.

Figure 10 integrates the study's central empirical dimensions by jointly visualizing quantile heterogeneity and stress conditioning. The shaded regions delineate structural segments of the digital economy distribution, while the divergence between low- and high-stress curves highlights regime dependence. The figure makes explicit that the largest welfare-relevant losses under stress occur in the lower tail, where FinTech credit ceases to function as an effective transmission channel.

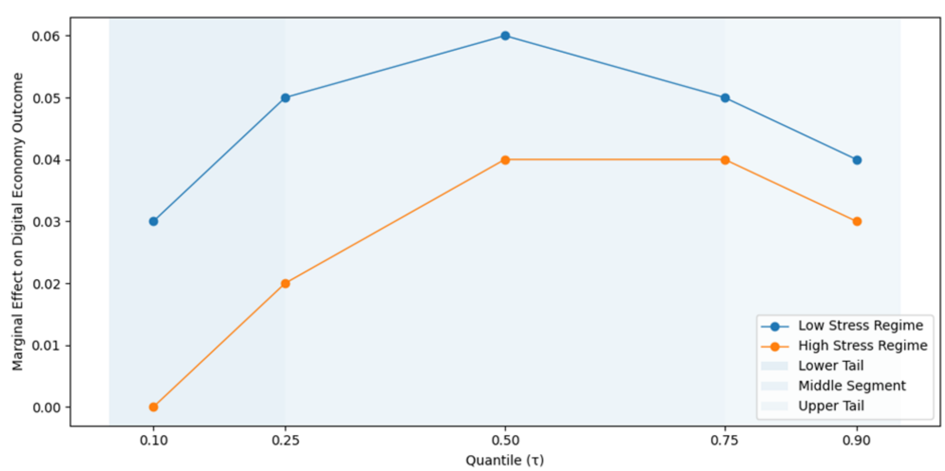

Figure 10 Integrated Quantile–Stress Effect Synthesis

At the same time, the relative stability of upper-quantile effects illustrates that digital maturity and institutional depth act as buffers against financial stress. This synthesis underscores the paper's key contribution: FinTech credit is neither uniformly pro-growth nor uniformly fragile. Its effectiveness depends critically on distributional position and macro-financial conditions, a nuance that cannot be captured through average-effect models.

Table 10 translates the empirical findings into actionable policy and strategic insights by aligning distributional positions with differentiated intervention priorities. For lower-tail economies, the evidence suggests that expanding FinTech credit in isolation is unlikely to generate meaningful digital gains and may even exacerbate fragility under stress. Structural investments in infrastructure, trust, and regulation are therefore prerequisites for effective FinTech deployment.

Table 10 Policy and Strategic Implications by Distribution Segment

Distribution Segment	Observed FinTech Credit Effect	Role of Financial Stress	Policy and Strategic Implications
Lower tail (digitally constrained)	Weak or insignificant	Strongly negative	Prioritize digital infrastructure, consumer protection, and counter-cyclical support before credit expansion
Middle segment (emerging digital economies)	Strong and positive	Moderately negative	Leverage FinTech credit with supportive regulation and innovation incentives
Upper tail (digitally mature)	Positive but diminishing	Minimal attenuation	Focus on efficiency, risk management, and systemic resilience

In contrast, middle-segment economies represent the highest return zone for FinTech credit expansion, where digital readiness and elasticity are sufficiently developed to convert credit growth into sustained digital economic progress. Upper-tail economies, while resilient, face diminishing returns and should emphasize stability and risk containment. This segmentation-oriented interpretation reinforces the study's overarching conclusion that FinTech credit policy must be distribution-aware and stress-sensitive to avoid unintended divergence in the digital economy.

Conclusion

This study provides robust empirical evidence that FinTech credit growth exerts asymmetric and distribution-dependent effects on digital economy indicators when financial stress is explicitly accounted for. By employing a panel quantile regression framework, the analysis demonstrates that FinTech credit is most effective in economies located around the middle of the conditional digital economy distribution, while its impact is weak or negligible in lower-tail economies and exhibits diminishing returns at the upper tail. These findings confirm that average-effect models obscure critical heterogeneity and risk mischaracterizing the role of FinTech credit in digital economic development.

The results further reveal that financial stress fundamentally reshapes FinTech credit transmission mechanisms. Elevated stress conditions significantly weaken the marginal contribution of FinTech credit growth, particularly among digitally constrained economies, where the effectiveness of credit nearly collapses. In contrast, digitally mature economies exhibit substantial resilience, maintaining positive FinTech effects even during adverse financial regimes. This asymmetric stress response implies that FinTech credit can unintentionally reinforce digital divergence during crises if not supported by adequate institutional and regulatory safeguards.

From a policy and strategic perspective, the study underscores the necessity of distribution-aware and stress-sensitive FinTech governance. Credit-based FinTech expansion should not be treated as a universal solution for digital transformation; instead, it must be complemented by investments in digital infrastructure, regulatory quality, and financial stability mechanisms, particularly in vulnerable economies. Future research may extend this framework by integrating micro-level platform data, exploring nonlinear regime-switching dynamics, or assessing welfare implications of FinTech credit cycles under extreme stress scenarios.

Declarations

Author Contributions

Conceptualization: M.K.A. and M.A.A.; Methodology: M.A.A.; Software: M.K.A.; Validation: M.K.A. and M.A.A.; Formal Analysis: M.K.A. and M.A.A.; Investigation: M.K.A.; Resources: M.A.A.; Data Curation: M.A.A.; Writing Original Draft Preparation: M.K.A. and M.A.A.; Writing Review and Editing: M.A.A. and M.K.A.; Visualization: M.K.A.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

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

Funding

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

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

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

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