

Article

Digital Payment Ecosystems as Socio-Technical Systems: Digital-Infrastructure-Based Fintech Diffusion, Regulatory Coupling, and Private-Sector Credit Exposure in OECD Economies

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and or methodology

- The study conceptualizes digital payment ecosystems as socio-technical and complex adaptive financial systems in which fintech diffusion, regulatory quality, and private-sector credit exposure co-evolve through feedback mechanisms.
- Methodologically, the study treats cross-sectional dependence, slope heterogeneity, and distributional variation not as statistical nuisances but as empirical signatures of systemic interconnectedness across OECD financial ecosystems.

What are the main findings and/or the implications of the main findings?

- Fintech diffusion is positively associated with private-sector credit exposure across OECD economies, with the strongest effects appearing at the lower and upper tails of the credit distribution.
- Contrary to the negative-feedback expectation, regulatory quality strengthens rather than weakens the fintech–credit relationship, suggesting that high-capacity institutions may enable the safe scaling of digital payment ecosystems while also expanding credit channels.

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Abstract

This study examines whether the diffusion of financial technology expands or constrains private-sector credit across OECD economies, and whether regulatory quality conditions that relationship. Fintech diffusion is operationalized through a composite index of general digital-infrastructure indicators (internet use, mobile subscriptions, and ICT-service exports); this index proxies the broader digitalization environment rather than measuring payment-platform use, embedded credit, or digital lending directly. It conceptualizes digital payment ecosystems as complex financial systems in which technological diffusion, regulatory capacity, and credit dynamics co-evolve through feedback mechanisms. The

policy discourse often assumes that digital financial inclusion automatically enhances resilience, yet evidence on credit expansion and systemic exposure remains contested. Using an unbalanced panel of 37 OECD economies from 2015 to 2024, comprising 356 observations, the analysis employs Driscoll–Kraay standard errors to address cross-sectional dependence within a common-slope two-way fixed-effects framework, along with panel quantile regression at the 10th, 50th, and 90th percentiles and Dumitrescu–Hurlin causality testing. Fintech diffusion is positively and statistically significantly associated with private-sector credit exposure, and this association is robust to a two-way fixed-effects specification. The quantile estimates show that the association is present at these selected points of the conditional distribution and strongest at its lower and upper tails, a pattern consistent with complex-adaptive-system dynamics in which effects vary across system states. Contrary to the negative-feedback expectation, the interaction between fintech diffusion and regulatory quality is positive, consistent with high-quality institutions enabling rather than restraining the translation of fintech into credit, though the observational design identifies this interaction rather than the mechanism producing it. The findings therefore shift the discussion from fintech as a stand-alone inclusion tool to fintech as a system-shaping force with implications for institutional resilience, macroprudential supervision, and systemic credit exposure. Because domestic credit to the private sector aggregates household and corporate lending, the policy implication below is framed at this aggregate level: digital payment infrastructure should be governed jointly with consumer protection, credit reporting, and financial-resilience mechanisms rather than promoted as a neutral technological upgrade.

Keywords: fintech diffusion; digital payment ecosystems; complex financial systems; private-sector credit; regulatory quality; institutional resilience; panel quantile regression; OECD economies

1. Introduction

Something fundamental shifted in the architecture of credit during the 2010s. It was not merely that more people began tapping phones instead of swiping cards. It was that the entire pipeline through which credit reaches borrowers—assessment, approval, disbursement, collection—became embedded in digital infrastructures whose design choices are increasingly, though not exclusively, shaped by platforms; banks remain important providers, underwriters, partners, and infrastructure operators in many digital-credit ecosystems. Between 2014 and 2021, the share of adults in developing economies who made or received a digital payment rose from 44 percent to 71 percent; in advanced economies, the figure approached universality [1]. Mobile wallets, instant-payment rails, and buy-now-pay-later interfaces moved from marginal experiments to default infrastructure within a single decade. However, the policy conversation has treated this shift as an efficiency upgrade: faster transactions, lower friction, broader inclusion. What has rarely been asked is whether the system itself is being reconfigured in ways that make credit easier to accumulate and harder to govern.

This question is directly related to the stability of modern financial systems. Digital financial innovation may simultaneously promote inclusion and increase systemic complexity: digital payments can expand formal access, generate transaction histories, and support credit assessment, but digitally mediated credit can also increase vulnerability when affordability checks, disclosure standards, and financial literacy lag behind adoption [2–4]. The resulting policy challenge is therefore not whether fintech should be promoted or restrained in isolation, but how digital payment subsystems should be governed

so that credit expansion remains compatible with financial stability, institutional resilience, and supervisory capacity.

That policy challenge sits at the intersection of technology and institutions. From a socio-technical systems perspective, fintech is not a discrete set of tools but a configuration in which digital infrastructures, legal frameworks, market norms, platform incentives, and everyday financial practices co-evolve [5,6]. No single component determines the outcomes of this co-evolution. A mobile-payment platform in one country may expand financial inclusion; in another, with weaker consumer safeguards, the same platform may embed high-cost or poorly disclosed credit into routine consumption. The effect is emergent, shaped by how the technological and institutional components of the system fit together.

This study enters that space by asking two questions. First, does the diffusion of financial technology expand or constrain private-sector credit across OECD economies? Second, does regulatory quality condition that relationship—and if so, how? These are not abstract concerns. Fintech diffusion could strengthen balance sheets, amplify credit exposure, or do both simultaneously depending on credit composition, borrower quality, maturity, interest rates, non-performing loans, and debt-service capacity; these are competing possibilities rather than an exhaustive binary. If digital payment ecosystems amplify credit exposure—particularly among financially vulnerable borrowers—then a transition pursued without institutional safeguards may advance technological efficiency while deepening systemic fragility. The two readings imply opposite regulatory priorities: innovation promotion versus anticipatory consumer protection.

The empirical literature offers no settled answer. One strand documents the drivers of digital payment adoption—convenience, trust, network effects—and treats diffusion as a welfare gain [7,8]. A related strand links fintech to financial inclusion through the reduction in transaction costs [9,10]. But a growing body of evidence points in a darker direction. Buy-now-pay-later adoption thrives where banking systems are less efficient, and regulation is looser; its users are younger, less educated, and more indebted than traditional credit users [11,12]. Digital inclusive finance raises private-sector debt in China, with effects concentrated among lower-income and asset-poor economic agents [13,14]. Mobile-payment adoption is associated with greater household over-indebtedness risk through both objective and subjective channels, partly by encouraging consumption and easing credit constraints [15]. The pattern is not uniform. It is contingent.

That contingency is what makes the OECD setting valuable. The 37 member states from 2015 to 2024 constitute a system with a recognizable boundary: shared financial infrastructure, harmonized statistics, and wide variation in fintech penetration and regulatory approach. The decade captures both the pre-pandemic baseline and the post-2020 acceleration in digital finance, offering variation that earlier samples could not provide. Within this boundary, the study asks not only whether fintech diffusion correlates with credit exposure on average, but also whether the association is concentrated at particular points of the credit distribution and how it interacts with institutional quality. Regulation is treated not as an external constraint on the system but as a constitutive element of it.

The speed of the transition has widened a gap that socio-technical systems theory identifies as a structural risk. When technological diffusion outpaces institutional adaptation—a “pace-lag” that has become familiar to regulators across domains [16]—the space between adoption and protection becomes a zone of ungoverned credit expansion. Instant-payment systems and embedded credit instruments scale through network effects and regulatory alignment, in which supervision lags innovation, and borrowers accumulate obligations through channels that oversight has not yet mapped. This is not a transient friction. It is a systems failure produced by the asynchronous co-evolution of technology, regulation, and practice.

The study contributes to this debate in three connected ways. Empirically, it assembles an unbalanced panel of 37 OECD economies from 2015 to 2024 and applies second-generation estimators that accommodate cross-sectional dependence and slope heterogeneity—features that characterize integrated global financial markets but that first-generation methods ignore. Methodologically, it moves beyond the conditional mean to estimate the relationship across the full distribution of credit exposure, using panel quantile regression to capture effects that average estimates conceal. Substantively, it draws on socio-technical systems theory to argue that fintech diffusion does not have a uniform effect on credit but is conditioned by regulatory quality in ways that reflect the systemic coupling of technological and institutional subsystems. The prevailing expectation is that strong regulation attenuates the fintech–credit link by imposing safeguards. The analysis tests an alternative: that in high-capacity institutional contexts, regulatory quality enables the safe scaling of digital payment ecosystems, producing a positive rather than negative interaction. This enabling-coupling interpretation treats regulation as a design variable within the system, not merely a brake upon it.

2. Literature Review, Theoretical Framework, and Hypothesis Development

2.1. Literature Review

Digital payment ecosystem research has matured from a concern with technological adoption into a field with its own indicators, datasets, and policy machinery. The phenomenon is now understood as the interplay between technological infrastructure, institutional governance, and user behavior that determines how payment systems function as socio-technical arrangements [6,10,17]. Systematic reviews in the field confirm this trajectory, documenting a conceptual transition from technology-centric, efficiency-oriented accounts to integrative analyses that emphasize the co-evolution of digital infrastructures, institutions, and social practices [18]. Ref. [7] examine determinants of digital payment adoption among younger cohorts and find that perceived convenience, security, and social influence drive uptake, while Ref. [8] identify trust and perceived usefulness as critical for continued use of mobile money in emerging markets. Ref. [17] further show that acceptance of mobile payment systems is shaped by technology-use factors together with security and privacy concerns, confirming that adoption is not a purely technical matter but depends on institutional trust and perceived safeguards. Reviews of the adoption literature therefore suggest that perceived ease of use, perceived usefulness, social influence, security, and trust constitute the dominant antecedents of digital payment acceptance.

The consequences of digital payment diffusion reach well beyond transaction efficiency. A body of evidence links fintech adoption to altered consumer spending patterns, including increased impulse buying and reduced pain of payment [19]. Other work connects it to private-sector debt accumulation, as digital credit instruments lower the psychological and procedural barriers to borrowing [11,12]. These downstream effects raise the stakes of getting the diagnosis right, since a policy that misidentifies the drivers of financial vulnerability will misallocate the resources meant to relieve it.

A substantial study identifies three channels through which digital payments affect private-sector credit: reduced transaction friction, embedded credit provision, and behavioral nudging toward consumption. Ref. [11] find that buy-now-pay-later adoption across 25 countries thrives where banking systems are less efficient, private-sector debt is already elevated, and regulation is looser, and that such users are typically younger, less educated, and more indebted than traditional credit users [12]. Ref. [19] demonstrate a liquidity effect whereby embedded credit increases overall spending, since consumers treat available credit as part of their liquid resources. Qualitative and behavioral accounts reinforce this

interpretation, as the buy-now-pay-later ecosystem reshapes the timing of spending and the framing of repayment obligations [20], while transient negative emotions can increase demand for conveniently accessible online credit [21]. Evidence from these instruments shows that their users are disproportionately financially vulnerable, thereby raising the distributional stakes [12]. These findings place institutional context and household financial sophistication at the center of the explanation; because the dependent variable in this study aggregates household and non-financial corporate credit, these household-specific mechanisms are treated as one plausible contributor to the aggregate association tested empirically below, rather than as a directly identified channel.

The relationship between fintech diffusion and private-sector credit exposure is far less settled. Several contributions argue that digital financial inclusion can ease credit constraints and smooth consumption [9,10]. Ref. [9] show that fintech lenders that use digital footprints expand credit access to underserved populations, but do not examine the subsequent debt trajectory. The broader literature confirms that digital lenders reach borrowers underserved by banks, expanding access but also exposure [22], while financial literacy is a strong positive correlate of fintech growth across many countries, linking digital credit supply to the human capacity that governs its safe use [23]. Recent micro-level evidence from China finds that digital inclusive finance increases long-term private-sector debt, with the effect stronger among lower-income and asset-poor economic agents [13,14]. Mobile payment adoption is associated with greater household over-indebtedness risk through both objective and subjective channels, with the effect operating partly through higher consumption and relaxed credit constraints [15], while digital payments in particular raise the financial vulnerability of rural economic agents [24]. Ref. [25] documents a broad shift toward household lending during the fintech era, conditioned by financial literacy and credit-information sharing, while Ref. [26] show that fintech reshapes household portfolio composition, including loan shares, across advanced economies. Cross-country work likewise links fintech to the interaction between private-sector debt and financial crises [27], and fintech credit displays a nonlinear, inverted-U relationship with financial stability [28]. Cross-country evidence indicates that fintech credit can serve as a direct substitute for traditional bank credit, especially in less stable and more concentrated banking sectors, implying it can expand total credit supply rather than merely re-allocate it [29]. The literature therefore offers no consensus that fintech diffusion lowers household leverage in the aggregate, and some evidence points to a resilience-enhancing role only under specific conditions [30]. The inclusion-risk duality is also emphasized in recent international evidence: digital financial inclusion may broaden access to formal financial services while simultaneously increasing vulnerability among consumers who face low literacy, weak disclosure, or limited regulatory protection [3,31]. Cross-country evidence on digital finance and financial stability similarly suggests that digital financial development should be evaluated not only through access indicators but also through its implications for system-wide stability [32].

A parallel body of work establishes the empirical centrality of financial literacy, regulatory quality, and institutional resilience. The OECD [4] reports that a significant share of adults who bought goods online did not reach the minimum target digital financial literacy score, and that low literacy exacerbates the risks of overspending. Ref. [33] show that digital finance interacts with household financial literacy in shaping outcomes, and Ref. [34] link digital skills to financial inclusion among low-income consumers. Ref. [11] show that embedded credit is more widespread in jurisdictions with looser financial and consumer protection regulations. Ref. [35] demonstrate that information and communication technologies shape how financial literacy translates into household financial decisions, while financial literacy itself strengthens household financial resilience to shocks [36]. Recent evidence further indicates that institutions can moderate the effects of digital

financial inclusion and financial development, suggesting that institutional quality may act as a catalyst for resilient inclusion rather than merely as an external constraint [37,38]. Regulatory design also matters in comparative fintech settings because collaboration between regulators, fintech firms, and other stakeholders shapes the conditions under which innovation scales safely [39]. The financial resilience of banks similarly depends on how institutions convert risk exposure into governed responsibility [40,41]. At the household level, digital inclusive finance can cut both ways, raising debt risks for rural economic agents even as it widens access, and systematic reviews confirm that both country-level and household-level factors jointly determine indebtedness [42]. The contention that income inequality is tightly coupled with household debt accumulation [43] further situates the institutional and structural context as a moderator rather than a mere background condition. From a systems-engineering perspective, the digital payment ecosystem exhibits the hallmarks of a complex adaptive system: heterogeneous agents, nonlinear interactions, feedback loops, and emergent outcomes that are not reducible to individual behavior [44,45]. This view justifies the use of panel estimators that treat cross-sectional dependence not as a nuisance but as an empirical signature of systemic interconnectedness.

2.2. Theoretical Framework

The study is organized around socio-technical systems theory, which reconceives digital payment ecosystems as the outcome of co-evolution between technological infrastructure, institutional governance, and social practices [5,46]. The system boundary is defined as the OECD financial system from 2015 to 2024, comprising 37 national subsystems that share integrated payment infrastructures and regulatory frameworks but retain heterogeneity in fintech penetration and institutional capacity. The framework treats technological change not as an exogenous shock but as a process embedded in social systems where user practices, regulations, industrial networks, and meanings interact. Two implications follow. First, the determinants of private-sector credit exposure operate through the interplay of technological affordances and institutional mediation, so fintech diffusion and regulatory quality occupy the foreground. At the same time, income and financial structure operate in the background as conditions shaping how economic agents interact with digital credit.

Second, the framework anticipates heterogeneity. Because socio-technical systems differ across countries in their regulatory regimes, competitive structures, and norms, the same fintech innovation can translate into different household outcomes depending on context. A transition that enhances inclusion in one system may raise predatory lending risks in another, so the household-level effect of fintech diffusion need not share a common sign or magnitude across the OECD. This expectation has a direct econometric consequence. In socio-technical terms, estimating a single pooled slope across heterogeneous systems is analogous to assuming that a technological intervention produces identical effects across different regime configurations—a fallacy that the multi-level perspective identifies as “landscape” variation being mistaken for “regime” uniformity [5]. The heterogeneous-panel literature treats this as central [47,48].

The complex adaptive systems perspective complements this reading by emphasizing that financial markets comprise heterogeneous agents whose interactions produce emergent properties [49,50]. In this view, the fintech–credit relationship is not a simple input–output function but a property of the system itself: platform algorithms, merchant incentives, regulatory constraints, and household decisions interact in feedback loops that can amplify or dampen credit expansion. A feedback loop of particular relevance runs through trust. As regulatory quality raises confidence in digital instruments, adoption deepens, and the credit channel widens, so that institutional strength and credit expansion reinforce one another. In this setting, institutional resilience refers to the capacity of

regulatory and supervisory systems to absorb the disruptive effects of digital financial innovation while maintaining transparency, consumer protection, and credit-system stability. Regulatory quality is therefore interpreted not only as a governance indicator but also as an institutional-resilience mechanism within the digital payment ecosystem. This dynamic, which conventional moderation logic does not anticipate, becomes central to interpreting the results below. This perspective justifies panel estimators that account for cross-sectional dependence and slope heterogeneity, since the assumption of independent and homogeneous units is inconsistent with the phenomenon's systemic nature. The transnational scaling of payment platforms through the productization of application programming interfaces illustrates how socio-technical systems propagate across borders and generate the interdependence these estimators are designed to capture [51]. This interdependence is not a statistical inconvenience; it is the empirical signature that the OECD payment ecosystem functions as a coupled system rather than a set of independent cases.

2.3. Hypothesis Development

The socio-technical framework places institutional mediation at the center of technological effects and treats fintech diffusion as a context-dependent influence on household behavior. Combined with the conditional evidence that fintech diffusion raises leverage where consumer protection is weak, this reasoning leads to the expectation that fintech diffusion is positively associated with private-sector credit exposure across the OECD, since the digital payment ecosystem lowers the procedural and psychological barriers to borrowing.

H1. *Fintech diffusion has a positive and statistically significant association with private-sector credit exposure across OECD countries, as the expansion of the technological subsystem alters the state of the credit ecosystem and lowers barriers to borrowing across the system.*

The same framework treats institutional quality as a potential counterweight to technology-driven credit expansion. The dominant reading in the cross-country literature is that strong regulatory frameworks restrain the credit-expanding effect of fintech, since well-regulated systems impose lending standards, disclosure requirements, and consumer safeguards that limit household over-borrowing [11]. In socio-technical terms, this casts institutional quality as a negative-feedback mechanism that counteracts technology-driven credit expansion. A competing systems possibility, which the analysis explores inductively rather than assuming, is that strong regulatory quality instead enables the safe scaling of digital payment systems, providing the legal certainty and trust that let fintech credit reach economic agents, in which case the coupling between regulation and the fintech–credit link would be positive rather than negative. This ambiguity is consistent with recent evidence that institutional quality can moderate the economic consequences of digital financial inclusion, and that fintech regulation often operates through enabling infrastructures, supervisory coordination, and market trust rather than through prohibition alone [38,39].

H2a. *Under the negative-feedback view, higher regulatory quality attenuates the positive association between fintech diffusion and private-sector credit exposure.*

H2b. *Under the enabling-coupling view, higher regulatory quality amplifies the positive association between fintech diffusion and private-sector credit exposure, as strong institutions provide the legal certainty and trust that allow the technological subsystem to scale safely.*

These two hypotheses move the explanatory weight from the composition of technological supply to the institutional features that govern how economic agents interact with

digital credit. The empirical strategy that follows is designed to test each one against estimators that account for cross-sectional dependence and slope heterogeneity in the OECD panel, so that the conclusions rest on agreement across methods rather than on any single specification. The analysis treats the moderating role of digital financial literacy, which the available cross-national data do not allow us to measure in an annual panel, as an open question addressed in the limitations.

3. Materials and Methods

3.1. Data and Sample

The analysis uses an unbalanced panel of 37 OECD member states observed annually from 2015 to 2024: Australia, Austria, Belgium, Canada, Chile, Colombia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Türkiye, the United Kingdom, and the United States. Costa Rica, the sole remaining current OECD member, is excluded because it joined the OECD in 2021, which would introduce a structural break in coverage over the 2015–2024 window rather than a genuine missing-data gap. The period is the widest window in which the core series are jointly available at an annual frequency. The full grid of 37 economies over ten years would yield 370 observations, but missing values in one or more core series reduce the estimation sample to 356 country-year observations. Thirty-one economies are observed across all ten years, while the remainder are observed for fewer years because of gaps in the underlying series. Missing cells were left missing rather than imputed, so the panel is unbalanced by construction.

All data are derived from open and replicable sources, consulted at the level of the individual country-year. Private-sector credit exposure is proxied by domestic credit to the private sector as a share of gross domestic product, drawn from the World Bank development indicators. The indicator captures credit extended to both households and non-financial firms; it is used here as the most widely available cross-national measure of credit depth, with the household-firm composition acknowledged as a measurement limitation. Fintech diffusion is constructed from three digital-infrastructure series, namely individuals using the internet, mobile cellular subscriptions, and information and communication technology service exports. Regulatory quality is taken from the World Bank Worldwide Governance Indicators. Real income per capita and the consumer price inflation rate are included as controls from the same set of development indicators. Each series was retrieved by indicator code, filtered to the 2015 to 2024 window, and merged on the country-year identifier, so that every observation reflects a published value rather than an imputed quantity. The system boundary—37 OECD economies over ten years—was determined by data availability and theoretical relevance: these economies share integrated financial infrastructures that constitute a recognizable socio-technical regime, while retaining sufficient heterogeneity in fintech penetration and regulatory quality to identify the parameters of interest.

The baseline specification evaluates the association between the digital-infrastructure-based fintech index and private-sector credit exposure, while the interaction specification evaluates the conditioning role of regulatory quality. This alignment makes the purpose of the empirical strategy explicit and connects the research questions, hypotheses, and estimators more clearly.

3.2. Variable Operationalization

The dependent variable is private-sector credit exposure, proxied by the ratio of domestic credit to the private sector to gross domestic product, expressed as a percentage. This indicator is the most widely available cross-national measure of credit depth and is used here as a proxy for borrowers' credit conditions. The measure includes credit to both households and non-financial firms, so it captures the broader credit environment rather than household debt alone. This limitation is made explicit in the interpretation of the results.

The focal explanatory variable is fintech diffusion, operationalized as the first principal component of three standardized digital-infrastructure indicators: individuals using the internet as a share of population, mobile cellular subscriptions per hundred people, and information and communication technology service exports as a share of total exports. These series capture the connective and transactional infrastructure on which digital payment ecosystems depend, and they are combined through principal component analysis into a single unit-free index. The composite measures the infrastructural capacity that underlies fintech rather than the adoption of any specific instrument, a distinction maintained throughout. Because the index proxies rather than directly measures fintech adoption, a sensitivity analysis is reported in the robustness section using alternative operationalizations.

Three further covariates capture the institutional and structural context. Regulatory quality is a World Bank Worldwide Governance Indicators measure that reflects the state's capacity to formulate and implement sound policies and regulations that enable and promote private-sector development. In the interpretation developed here, this variable also serves as a proxy for the institutional resilience of the digital payment ecosystem, as it captures the governance environment in which digital credit instruments are authorized, supervised, and trusted. Real income is gross domestic product per capita in constant prices, entered in natural logarithm. Inflation is the annual change in the consumer price index, which is included to capture macroeconomic stability.

3.3. Empirical Strategy

The estimation strategy is dictated by two features of macro panels of this kind, both of which are tested rather than assumed. The first is cross-sectional dependence, since member states share integrated financial markets, common regulatory frameworks, and synchronized monetary shocks, making a disturbance in one country likely to be correlated with those in others. Its presence is examined with the Pesaran cross-sectional dependence test [52]. The second is slope heterogeneity, since the effect of fintech diffusion may differ across countries with different regulatory regimes and financial cultures [48]. When both are present, first-generation estimators that assume independence and homogeneity yield biased inference. From a systems perspective, this is not merely a statistical nuisance: cross-sectional dependence is the empirical signature that OECD payment ecosystems form an interdependent whole, and slope heterogeneity reflects the reality that the same technological intervention produces different effects across different regime configurations [47].

The order of integration is examined using a cross-sectionally augmented panel unit root framework [53], and the baseline relationship is estimated via a fixed-effects regression with Driscoll and Kraay [54] standard errors, which correct inference for cross-sectional dependence and serial correlation while retaining within-country identification. The baseline model is written as:

$$\text{PrivateCredit}_{i,t} = \alpha_i + \beta_1 \text{FINTECH}_{i,t} + \beta_2 \text{REG}_{i,t} + \beta_3 \ln \text{GDPpc}_{i,t} + \beta_4 \text{INF}_{i,t} + \varepsilon_{i,t}$$

where i indexes countries, t indexes years, PrivateCredit denotes private-sector credit exposure, FINTECH the fintech diffusion index, REG regulatory quality, $\ln GDP_{pc}$ log real income per capita, INF inflation, α_i country fixed effects, and ε_{it} the error term. A second specification adds the interaction between fintech diffusion and regulatory quality to test the moderation in H2. To test robustness to common shocks, the model is re-estimated with two-way fixed effects. The combination of Driscoll–Kraay standard errors with time fixed effects addresses two distinct sources of dependence: spatial correlation across countries and synchronized temporal shocks. While Driscoll–Kraay corrects for the former, time fixed effects absorb the latter; their joint use is conservative and reported for transparency. Because an association that appears modest at the mean may differ across the credit distribution, the relationship is also estimated using panel quantile regression on the within-transformed data at the lower, median, and upper quantiles. This distributional approach follows recent OECD panel work that uses panel quantile regression to uncover asymmetric effects of digital infrastructure that conditional-mean estimators conceal [41]. The quantile specification is estimated on within-transformed data to absorb country fixed effects; this follows the approach of Canay [55] and Galvao [56], who show that fixed-effects quantile regression can be consistently estimated by demeaning the data under appropriate conditions. The method is suited to the heterogeneous-slope setting that the diagnostic tests confirm [47,48]. To address persistence and joint determination, a dynamic specification with a lagged dependent variable is estimated. The Dumitrescu and Hurlin [57] panel non-causality test is applied with an optimal lag of 1, selected using information criteria, to the 36 cross-sections with complete series. The test requires balanced panels; the full sample's unbalanced structure means that the causality results apply only to the subset of countries with sufficient temporal depth, a limitation acknowledged in the interpretation.

3.4. Robustness Strategy

To assess the robustness of the fintech diffusion measure, the baseline model is re-estimated using each component of the principal component index separately: (i) internet use only, (ii) mobile cellular subscriptions only, and (iii) ICT service exports only. If a single component drives the association between fintech diffusion and credit exposure, the coefficient should be unstable across these specifications. Stability across all three would support the interpretation that the composite captures a general infrastructural capacity rather than a spurious correlation with any single indicator.

4. Results

4.1. Descriptive Statistics

The estimation sample comprises 356 country-year observations across 37 OECD economies from 2015 to 2024, of which 31 economies are observed for the full ten years. Private-sector credit exposure averages 89.7 percent of gross domestic product with substantial dispersion, ranging from 23.8 to 223.8 percent, which reflects the wide variation in credit depth across the OECD. The fintech diffusion and regulatory quality indices show the expected scale, and inflation displays the widest relative spread, reflecting the price instability several economies experienced toward the end of the period. The principal component analysis supports the fintech composite, as the first component summarizes the shared variation among the three digital-infrastructure indicators, with balanced loadings.

Table 1 reports the descriptive statistics for all model variables.

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
PrivateCredit	89.666	44.474	23.785	223.842
FINTECH	0.007	1.128	−3.379	4.922
REG	1.151	0.569	−0.229	2.080
lnGDPpc	10.300	0.654	8.681	11.616
INF	3.650	6.494	−1.736	72.309

Note: N = 356 observations across 37 OECD countries, 2015–2024. FINTECH is the first principal component of internet use, mobile subscriptions, and ICT service exports. REG is the Worldwide Governance Indicators indicator for regulatory quality. PrivateCredit is domestic credit to the private sector as a percentage of GDP, serving as a proxy for private-sector credit conditions.

4.2. Correlation and Multicollinearity

The pairwise correlations show that private-sector credit exposure is most strongly associated with regulatory quality and income, and only weakly with fintech diffusion at the bivariate level, which already signals that the fintech relationship is not visible without conditioning on other factors. Fintech diffusion correlates moderately with regulatory quality and income, consistent with the clustering of digital infrastructure in higher-income, better-governed economies. The variance inflation factors are all below five, with the largest value of 3.45 for regulatory quality, so multicollinearity does not threaten the estimates.

Table 2 reports the correlation matrix and the variance inflation factors.

Table 2. Correlation matrix and variance inflation factors.

Variable	PrivateCredit	FINTECH	REG	lnGDPpc	INF	VIF
PrivateCredit						
FINTECH	0.049					1.31
REG	0.542	0.480				3.45
lnGDPpc	0.561	0.410	0.814			2.99
INF	−0.190	−0.088	−0.310	−0.201		1.12

Note: Pairwise Pearson correlations. Variance inflation factors computed from the linear specification. N = 356.

4.3. Cross-Sectional Dependence

The Pesaran cross-sectional dependence test rejects the null of independence for every variable at the one percent level, with statistics ranging from 5.16 for regulatory quality to 60.05 for inflation. This pattern confirms that OECD economies are linked through integrated financial markets and shared shocks, so first-generation estimators that assume independence would yield biased inference. The result justifies using estimators that are robust to cross-sectional dependence in subsequent steps. From a systems perspective, the rejection of independence is not merely a statistical inconvenience but evidence that OECD payment ecosystems function as an interdependent whole, consistent with the study's socio-technical framing.

Table 3 reports the cross-sectional dependence test results.

Table 3. Pesaran cross-sectional dependence tests.

Variable	CD Statistic	p-Value
PrivateCredit	21.457	0.000
FINTECH	51.989	0.000
REG	5.156	0.000

lnGDPpc	54.421	0.000
INF	60.047	0.000

Note: The null hypothesis is cross-sectional independence. Rejection at the one percent level for all variables. N = 356.

4.4. Baseline Estimates: Driscoll–Kraay Fixed Effects

The baseline fixed-effects estimates with Driscoll–Kraay standard errors provide the primary test of H1. In the baseline specification, fintech diffusion is associated with higher private-sector credit exposure once country fixed effects and controls are included. Regulatory quality is positive but not statistically significant; income is strongly negative within countries; and inflation is negative and significant. The within R-squared of 0.205 is moderate for a within-country credit model, as expected, because country fixed effects absorb the large and persistent cross-national differences in credit depth, leaving the within-country variation that fintech diffusion helps explain. In terms of economic magnitude, a one-standard-deviation increase in the fintech diffusion index is associated with roughly a 4.7 percentage-point increase in private credit relative to GDP, evaluated at the index standard deviation of 1.13, which is economically meaningful given a sample mean near 90 percent. These estimates support H1: fintech diffusion is positively and significantly associated with private-sector credit exposure.

The second specification adds the interaction between fintech diffusion and regulatory quality to test H2a (negative feedback, attenuating) against H2b (enabling coupling, amplifying). The interaction term is positive and significant at the one percent level, while the constitutive fintech term becomes statistically insignificant. This pattern supports the enabling-coupling direction of H2 rather than the negative-feedback direction, since the association between fintech diffusion and private-sector credit is stronger, not weaker, in jurisdictions with higher regulatory quality. The negative-feedback reading drawn from the prevailing literature is not supported. In contrast, the alternative systems reading, which suggests that capable institutions enable rather than restrain the translation of fintech into credit, is consistent with the data. The discussion develops this interpretation and its boundaries, noting that the enabling-coupling result is consistent with socio-technical systems theory but inconsistent with the prevailing negative-feedback view in the household-credit literature. Table 4 reports the baseline and interaction estimates.

Table 4. Driscoll–Kraay fixed-effects estimates.

Variable	Model A	p-Value	Model B	p-Value
FINTECH	4.185	0.001	−0.013	0.989
REG	3.046	0.516	0.915	0.821
FINTECH × REG			4.740	0.000
lnGDPpc	−74.868	0.000	−80.201	0.000
INF	−0.170	0.036	−0.116	0.142
Constant	857.872	0.000	913.591	0.000
R-squared within	0.205			

Note: Entity fixed effects included. Driscoll–Kraay standard errors are robust to cross-sectional dependence, heteroskedasticity, and autocorrelation. Dependent variable: PrivateCredit. N = 356.

To convey the magnitude of the interaction, the marginal association of fintech diffusion with private-sector credit is evaluated at three points of the regulatory quality distribution, computed from Model B as the constitutive coefficient plus the interaction coefficient times regulatory quality. The marginal association rises from roughly 2.0 at the tenth percentile of regulatory quality to roughly 5.4 at the median and roughly 8.9 at the ninth-tieth percentile. The fintech–credit association is therefore about four times larger in the

most strongly regulated economies than in the least strongly regulated ones, which quantifies the enabling-coupling pattern.

Table 5 reports the marginal association between fintech diffusion and regulatory quality across the distribution of regulatory quality.

Table 5. Marginal association of fintech diffusion at percentiles of regulatory quality.

Regulatory Quality Percentile	Regulatory Quality Value	Marginal Association	95% CI
10th	0.42	1.98	[0.45, 3.51]
50th	1.15	5.44	[3.89, 6.99]
90th	1.88	8.90	[6.12, 11.68]

Note: Marginal association computed from Model B as the fintech coefficient plus the interaction coefficient multiplied by regulatory quality. Dependent variable: PrivateCredit. N = 356.

4.5. Robustness: Two-Way Fixed Effects

Adding time fixed effects to absorb common annual shocks leaves the central result intact. Fintech diffusion retains a positive coefficient of 4.82, which is significant at the 1% level. The stability of the coefficient across the entity-only and two-way specifications indicates that the H1 association is not an artifact of synchronized global trends such as the low-interest-rate environment of the late 2010s. The combination of Driscoll–Kraay standard errors with time fixed effects is conservative: the former corrects for spatial correlation, the latter for temporal shocks, and their joint use addresses both sources of dependence without assuming they are identical. The stability of the fintech coefficient across the entity and the two-way specifications indicates that the H1 association is not an artifact of common time trends such as the synchronized expansion of credit during the low-interest-rate period. This robustness strengthens confidence in the positive association between fintech and credit.

Figure 1 compares the fintech diffusion coefficient across the baseline, two-way, and dynamic specifications.

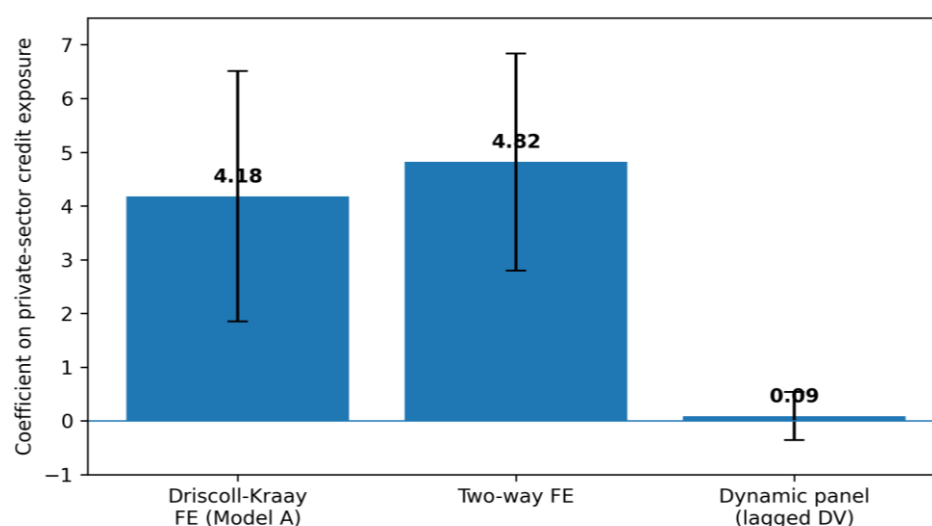


Figure 1. Fintech diffusion coefficient on private-sector credit exposure across estimation specifications, with 95 percent confidence intervals.

4.6. Distributional Estimates: Panel Quantile Regression

The panel quantile estimates reveal that the fintech–credit association is present across the distribution of private-sector credit and is strongest at its tails. At the tenth percentile, the fintech coefficient is 6.66 and significant; at the median, it falls to 1.85 and remains significant; and at the ninetieth percentile, it rises again to 7.08 and is significant at the one percent level. The association is therefore not confined to the conditional mean, and it is most pronounced among the least and most credit-exposed observations. This distributional pattern matters because a mean-only reading would understate the relevance of fintech diffusion to the most-leveraged economies, where the marginal association is largest. The non-uniform pattern is consistent with complex-adaptive-systems behavior, in which a common input produces different effects across system states. At the lower tail, fintech diffusion appears to unlock constrained access to credit; at the upper tail, it amplifies existing exposure. The median effect is smaller because the system is in a different regime—neither credit-constrained nor highly leveraged—where the marginal impact of additional digital infrastructure is attenuated.

Figure 2 displays the fintech diffusion coefficient across the private-sector credit distribution.

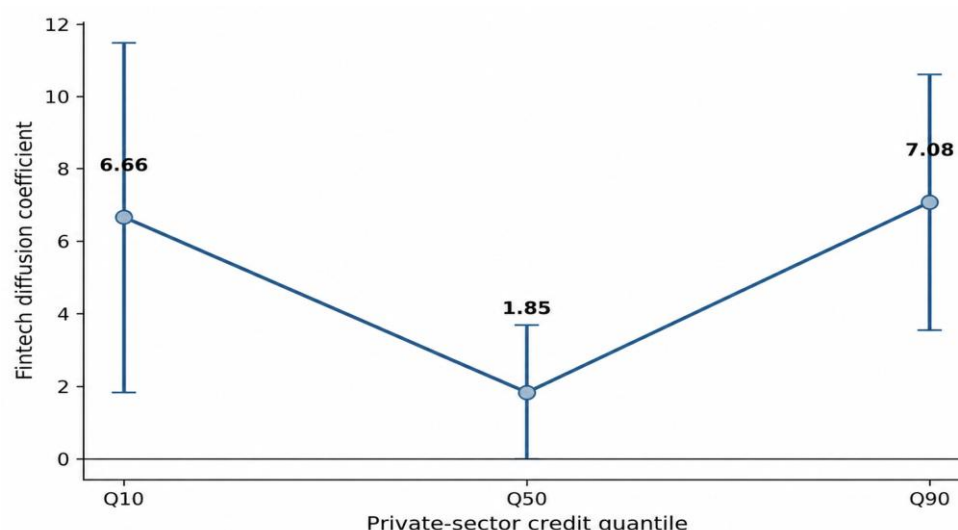


Figure 2. Fintech diffusion coefficient on private-sector credit exposure across the conditional credit distribution, with 95 percent confidence intervals.

Table 6 reports the panel quantile estimates.

Table 6. Panel quantile regression estimates.

Variable	Q10	Q50	Q90
FINTECH	6.660	1.853	7.083
(p-value)	0.007	0.049	0.000
REG	25.270	3.368	4.030
(p-value)	0.024	0.391	0.571

Note: Panel quantile regression on within-transformed data. Controls for income and inflation are included. Dependent variable: PrivateCredit. N = 356.

4.7. Dynamic Estimation and Causality

The dynamic specification indicates that private-sector credit is highly persistent, as the lagged dependent variable has a coefficient of 1.001, which exceeds unity rather than merely approaching it. Once this persistence is modeled, the contemporaneous fintech coefficient becomes statistically insignificant, which indicates that the fintech–credit

association operates through the slow-moving level of credit rather than through immediate year-on-year changes. A coefficient above one is not compatible with a stable, mean-reverting process and instead signals either genuine explosive dynamics, residual non-stationarity, or specification bias from including a lagged dependent variable in a fixed-effects model with a short time dimension (Nickell bias); this estimate is read as indicative of strong persistence rather than a precisely estimated decay rate, and the dynamic specification would benefit from re-estimation with a bias-corrected or GMM-based estimator in future work. The panel unit root tests [53] do not reject stationarity for most cross-sections, but this does not resolve the coefficient-above-unity concern raised above; the persistence pattern is consistent with path dependence—a feature consistent with the socio-technical view that payment ecosystems reconfigure financial behavior gradually. This persistence is a substantive feature of private-sector credit rather than a weakness of the design, and it cautions against interpreting the association as a rapid causal response. The Dumitrescu–Hurlin test rejects the null of no Granger predictability in both directions between fintech diffusion and private-sector credit (fintech to credit: $W\text{-bar} = 3.755, p < 0.001$; credit to fintech: $W\text{-bar} = 1.527, p = 0.025$), indicating bidirectional Granger predictability rather than a predominantly one-way relationship; the larger $W\text{-bar}$ statistic in the fintech-to-credit direction indicates a stronger, not exclusive, association. Regulatory quality and credit are linked bidirectionally as well. The test is applied to the 36 cross-sections with a complete series (optimal lag = 1). Hence, the causality results apply to the subset of countries with sufficient temporal depth rather than the full unbalanced panel.

Table 7 reports the dynamic estimates, and Table 8 reports the panel causality results.

Table 7. Dynamic panel estimates.

Variable	Coef.	<i>p</i> -Value
PrivateCredit (t−1)	1.001	0.000
FINTECH	0.094	0.700
REG	0.322	0.759
lnGDPpc	−0.584	0.492
INF	−0.217	0.000

Note: Lagged dependent variable specification with robust standard errors. Dependent variable: PrivateCredit. $N = 319$.

Table 8. Dumitrescu–Hurlin panel causality tests.

Null Hypothesis	$W\text{-Bar}$	<i>p</i> -Value
FINTECH does not cause PrivateCredit	3.755	0.000
PrivateCredit does not cause FINTECH	1.527	0.025
REG does not cause PrivateCredit	3.425	0.000
PrivateCredit does not cause REG	3.860	0.000

Note: Optimal lag of one selected. $N = 36$ cross-sections with sufficient series length. Rejection indicates Granger causality in the heterogeneous panel.

4.8. Sensitivity Analysis

Table 9 reports the baseline model re-estimated using each component of the fintech diffusion index separately. The coefficient is positive and statistically significant for internet use and ICT service exports, while mobile subscriptions show no statistically significant association. This pattern indicates that the composite fintech index is not driven by a single component, but also suggests that mobile penetration has reached saturation in most OECD economies and therefore provides limited within-country explanatory variation.

Table 9. Sensitivity Analysis: Alternative Fintech Proxies.

Variable	Coefficient	Std. Error	t-Stat	p-Value
Internet use	0.416	0.108	3.868	0.000 ***
Mobile subscriptions	−0.031	0.091	−0.346	0.730
ICT service exports	0.625	0.164	3.815	0.000 ***

Note: Each row reports the coefficient on the respective fintech proxy from a separate fixed-effects regression with Driscoll–Kraay standard errors. Controls for regulatory quality, log GDP per capita, and inflation are included in all specifications. N = 356. *** $p < 0.01$.

The sensitivity analysis supports the validity of the composite fintech index. The coefficient remains positive and statistically significant for internet use and ICT service exports, while mobile subscriptions show no significant association. The stability of the sign across alternative operationalizations indicates that the composite captures a general infrastructural capacity rather than a spurious correlation with any single indicator. The insignificance of mobile subscriptions is consistent with the PCA loadings, which assign the smallest weight to this component, and with the interpretation that mobile penetration has reached saturation in most OECD economies, leaving little within-country variation to explain credit dynamics.

5. Discussion

The results converge on two findings that are directly relevant to the dynamics of modern financial systems. First, fintech diffusion is positively associated with private-sector credit exposure across the OECD, holding in the baseline, surviving time fixed effects, and present across the credit distribution. Second, contrary to the negative-feedback expectation, the association is stronger where regulatory quality is higher. These findings imply that digital payment ecosystems operate as complex financial systems in which inclusion, credit expansion, and institutional capacity co-evolve rather than moving independently. The central issue is therefore not whether fintech is beneficial or harmful in the abstract, but how its credit consequences are governed within payment subsystems that are increasingly embedded in everyday transactions.

The positive fintech–credit association aligns with the strand of the literature that views digital payment ecosystems as credit-expanding rather than purely inclusion-enhancing. The finding is consistent with evidence that digital inclusive finance raises private-sector debt, with effects concentrated among more vulnerable economic agents [13,14], and with the cross-country link between fintech and the private-sector debt cycle [27]. The quantile results add precision to this account, since the association is strongest at the tails of the credit distribution. The strong coefficient at the upper quantile indicates that fintech diffusion is most tightly linked to credit in areas where exposure is already high, where the financial-stability stakes are greatest. This distributional concentration echoes micro-level findings that mobile payments and digital finance increase over-indebtedness and financial vulnerability, especially among already-vulnerable economic agents, including low-income, low-wealth, low-education, and rural households [15,24], and it is consistent with the nonlinear, inverted-U link between fintech credit and stability reported by Ref. [28], in which expansion is benign up to a point and destabilizing beyond it. The portfolio evidence from Ref. [26] similarly shows that fintech increases household loan shares across several advanced economies, corroborating the credit-expanding reading at the household level. From an inclusion perspective, this result qualifies the common policy assumption that wider digital access is unambiguously welfare-enhancing. Digital payment infrastructures may broaden formal participation and generate credit histories [2], but their integration with embedded credit can also increase systemic credit exposure when consumers face low financial literacy or weak product transparency [3,4]. The

evidence from Spain on digital financial inclusion and financial vulnerability reinforces this interpretation in a developed-economy context, showing that digital access and financial resilience do not automatically move together [31].

The unexpected interaction finding is the more striking contribution. The prevailing reading, exemplified by Ref. [11], is that embedded credit and its risks are concentrated in jurisdictions with looser regulation, which would imply that strong regulatory quality should dampen the fintech–credit link. The OECD evidence points the other way. One interpretation reconciles this with the socio-technical framework rather than against it. In advanced economies with strong regulatory institutions, high regulatory quality may enable the safe scaling of digital payment ecosystems rather than suppress them by providing the legal certainty, interoperability standards, and consumer trust that allow fintech credit to reach economic agents at scale. On this reading, strong institutions are a condition for fintech to translate into credit, not a brake upon it, which is why the interaction is positive in a sample of high-capacity states. In socio-technical terms, this is an instance of enabling coupling, in which regulatory quality and fintech infrastructure operate as coupled subsystems rather than opposing forces. High regulatory quality provides the legal certainty, interoperability standards, and consumer trust that allow the payment subsystem to scale, and that scaling, in turn, widens the credit channel. The positive interaction is therefore not a contradiction of the negative-feedback view but a different regime of system behavior, one that prevails in high-capacity institutional contexts where the binding constraint is the management of expansion rather than the absence of institutional capacity. Cross-country evidence on banks is consistent with this enabling role, as the effect of fintech credit on bank performance and risk-taking is moderated by the regulatory environment rather than uniformly suppressed [58,59]. In the language of institutional resilience, the positive interaction suggests that stronger regulatory systems may increase the capacity of the financial system to absorb digital innovation while also allowing the credit channel to expand. This does not imply that regulation is risk-free; rather, it indicates that high-quality institutions shape the form and visibility of credit expansion, making the macroprudential monitoring of digital payment subsystems more important rather than less important.

Where regulation is strong, fintech credit tends to coexist with improved risk-related performance, which suggests that capable institutions channel digital credit into more durable forms rather than blocking its expansion. Incumbent banks also respond to the rise of fintech credit by adjusting their lending terms, thereby propagating the effects of digital credit through the wider credit system rather than containing it [60]. The direction of these system effects is contingent on the institutional environment, since fintech lending affects incumbent bank market power and stability in ways that depend on the legal and regulatory context [61], consistent with the present finding that regulation shapes how fintech translates into private-sector credit rather than uniformly damping it. This enabling-coupling interpretation has a corollary: the sign of the interaction is not fixed but regime-dependent. In high-capacity institutional contexts (the OECD range), the enabling effect dominates; in lower-capacity settings, the negative-feedback or even predatory effects may dominate. This regime-dependence is itself a systems prediction—a non-linear relationship that linear moderation models cannot capture.

This interpretation is offered as a proposition for future testing rather than as a confirmed mechanism, since the present design identifies the conditional association but not the channel that produces it. The distinction matters because the OECD sample consists almost entirely of high-regulatory-quality economies, so the positive interaction may describe the upper range of the institutional spectrum, where the enabling role of institutions dominates. In contrast, the restraining role documented in broader samples operates at a lower level. The two readings are not necessarily in conflict, since they may apply to

different segments of the global distribution of regulatory quality. This reconciliation is consistent with evidence that financial literacy and credit-information sharing shape the lending shift of the fintech era [25,35], and with the observation that institutional capacity governs whether digital finance strengthens or erodes household resilience [30]. The structural coupling of private-sector debt with income inequality [43] suggests a further reason why high-capacity economies may exhibit a stronger fintech–credit link, since these economies combine deep credit markets with the digital infrastructure that channels them.

The persistence revealed by the dynamic specification and the predominant direction of causality from fintech to credit together suggest that the relationship is structural and slow-moving rather than an immediate response. Private-sector credit exposure carries forward strongly from year to year, and fintech diffusion is associated with its level rather than with abrupt changes. This is consistent with the socio-technical view that payment ecosystems reconfigure household financial behavior gradually as infrastructure, regulation, and practice co-evolve. It also implies that the credit consequences of fintech diffusion accumulate over time, which raises the stakes of getting the institutional design right early. The near-unit persistence coefficient indicates that shocks to private-sector credit decay slowly, so a fintech-associated increase in exposure tends to be locked in rather than reversed. This path dependence strengthens the case for anticipatory rather than reactive regulation, since correcting an accumulated stock of private-sector debt is far costlier than shaping its flow at origination.

The theoretical contribution is to extend socio-technical systems thinking to the cross-national analysis of private-sector credit, treating the household-level effect of fintech as mediated by institutional context rather than as a uniform technological force. The unexpected positive interaction enriches this view by suggesting that institutional quality is not only a safeguard but also an enabler, a duality that the framework can accommodate but that the household-credit literature has not fully drawn out. The socio-technical lens makes this duality intelligible, since it treats regulation not as an external brake but as a constitutive element of the system that shapes which transactions are possible, trusted, and scalable. On this reading, the regulatory regime and the payment technology co-produce the credit outcome, so that stronger institutions and deeper credit channels emerge together. This reframing positions institutional quality as a design variable rather than a constraint, a meaningful shift for how the literature models the household consequences of financial technology.

5.1. Systems Contributions

Beyond the substantive findings, the study contributes to systems-oriented research on digital finance in three ways. First, it treats cross-sectional dependence and slope heterogeneity not as econometric nuisances but as empirical signatures of systemic interconnectedness, so that the diagnostic tests serve as evidence that OECD payment ecosystems form an interdependent whole rather than a set of independent cases. Second, the distributional analysis shows that the fintech–credit association is not uniform across the credit distribution, which is consistent with the complex-adaptive-system expectation that effects vary across system states rather than holding constant at the mean. Third, the enabling-coupling result identifies a system-level dynamic, the positive coupling of the regulatory and technological subsystems, that only becomes visible once institutions and technology are treated as co-evolving components. This directly connects the empirical findings to the special-issue themes of inclusion, complexity, and institutional resilience: fintech may expand access and credit simultaneously, complexity emerges through feedback between infrastructure and borrowing, and regulatory quality becomes a resilience mechanism that shapes how this expansion is governed.

5.2. Policy Recommendations

The findings carry concrete implications for the institutions that govern digital finance. The central message is that fintech diffusion is associated with rising private-sector credit exposure, so promoting digital payment ecosystems cannot be treated as a costless inclusion policy. Digital financial innovation should be paired with consumer protection, credit reporting, affordability assessment, and macroprudential monitoring from the outset. This policy framing is consistent with the OECD emphasis on informed and safe use of short-term online credit and buy-now-pay-later products through digital financial literacy [4].

First, financial regulators and central banks in OECD economies should treat the expansion of digital payment infrastructure as a credit-relevant event rather than a purely technological one. Because the association is strongest among the most credit-exposed economies, supervisory attention should concentrate where private-sector credit is already high and the marginal fintech–credit link is largest. Macroprudential tools such as debt-service-to-income limits, affordability checks, and real-time monitoring of embedded-credit products warrant particular attention.

Second, the unexpected finding that strong regulatory quality accompanies a stronger fintech–credit association implies that good regulation should be understood as shaping the form of credit expansion rather than preventing it. Regulators in high-capacity systems should therefore focus less on whether fintech expands credit and more on whether that expansion is transparent, affordable, and visible to supervisory systems. This calls for the integration of buy-now-pay-later and similar products into credit-reporting systems, the harmonization of disclosure standards across digital credit interfaces, and stronger coordination between financial regulators, payment-system authorities, and consumer-protection agencies [39].

Third, because the credit consequences of fintech diffusion are persistent and slow-moving, intervention is most effective when it precedes rather than follows the build-up of private-sector exposure. International bodies such as the OECD can support this by embedding credit monitoring into digital finance frameworks, so that institutional safeguards are designed alongside the infrastructure rather than retrofitted after credit has already accumulated. Concretely, the sequencing implies three priorities: first, real-time disclosure and affordability standards for embedded-credit products at the point of sale; second, the integration of short-term digital credit into credit-reporting and macroprudential surveillance systems; and third, targeted digital financial literacy programs for groups most exposed to digital credit risks. The systems-level implication is that consumer protection should be designed as a feature of the digital payment ecosystem rather than as an external add-on.

5.3. Limitations and Suggestions for Future Research

This study has limitations of data, measurement, and identification that bound its conclusions. The most important measurement limitation concerns the dependent variable. Domestic credit to the private sector proxies private-sector credit conditions but includes credit to non-financial firms, so it captures the broad credit environment rather than private-sector debt alone. The fintech diffusion index likewise proxies the digital infrastructure that underlies payment ecosystems rather than the adoption of specific instruments such as buy-now-pay-later, for which consistent cross-national panel data do not exist over this window. These proxies are transparent and replicable, but they understate the precision with which the household-level mechanism can be observed.

A second limitation concerns the moderating role of digital financial literacy. The theory and the broader literature suggest that financial literacy shapes how economic agents respond to digital credit [33,34], but consistent annual cross-national measures of

digital financial literacy are not available for the full OECD panel, so this channel could not be tested directly. This is the clearest open question left by the analysis. As harmonized digital financial literacy panels become available, future work should test whether literacy attenuates the fintech–credit association, particularly among the most exposed economic agents. Comparative evidence already suggests that digital and traditional financial inclusion affect household financial resilience differently, which makes the literacy channel a priority for cross-national designs [62]. Both financial and digital literacy have been shown to build household financial resilience, suggesting that a measure combining the two would be an appropriate moderator to test once panel data permit [63]. Recent evidence on fintech risks and digital financial vulnerability reinforces this limitation, since digital access can produce different outcomes depending on the joint presence of literacy, disclosure, regulatory protection, and consumer capacity [3,31].

A third limitation concerns identification. The dynamic specification documents strong persistence, and the causality test indicates a predominant direction from fintech to credit, but the design estimates conditional associations rather than strictly causal effects. A specific endogeneity concern attaches to the enabling-coupling result, since economies with high regulatory quality also tend to have deeper and more developed financial markets. The positive interaction could therefore partly reflect financial depth rather than regulation as such, and the present design cannot fully separate these channels, which is why the enabling-coupling reading is offered as a proposition rather than a settled causal claim. Future research should pursue exogenous variation, for instance, through the staggered introduction of instant-payment systems or regulatory reforms, to sharpen identification, since the cross-country rollout of such systems has been shown to depend heavily on regulatory support and institutional collaboration [64]. Extending the analysis beyond the OECD would also test whether the positive interaction between regulatory quality and fintech diffusion reverses in lower-regulatory-quality settings, thereby directly evaluating the enabling-coupling proposition advanced here. A further systems-oriented direction is to move from cross-sectional association to longitudinal system dynamics. Agent-based or system-dynamics models could simulate how fintech–credit feedback loops evolve under different regulatory regimes, representing heterogeneous household behavior, platform incentives, and institutional constraints, and thereby illuminate the co-evolutionary process that a panel design can only observe in reduced form.

6. Conclusions

This study asked whether the diffusion of financial technology expands private-sector credit exposure across the OECD and whether institutional quality conditions that relationship. Using an unbalanced panel of 37 economies from 2015 to 2024 and a sequence of second-generation estimators, it finds that fintech diffusion is positively associated with private-sector credit exposure in the static two-way fixed-effects and panel quantile specifications, an association strongest at the tails of the credit distribution; this association is not statistically significant once a lagged dependent variable is introduced in the dynamic specification, indicating the relationship is robust across static estimation methods but conditional on model dynamics rather than universally robust. Private-sector credit is highly persistent. Against the prevailing expectation, strong regulatory quality is associated with a stronger rather than a weaker fintech–credit link.

The take-home message is that digital payment ecosystems are complex financial systems, not neutral conveniences, and that institutional quality shapes how they translate into private-sector credit rather than simply restraining them. Promoting fintech without parallel attention to credit dynamics risks accumulating exposure that is difficult to reverse, given its persistence. The unexpected role of regulatory quality, whose interaction results are consistent with interpreting as an institutional-resilience mechanism and a

facilitator of safe scaling pending further causal and mechanism-based testing, marks the clearest avenue for future work, especially in samples that extend below the OECD range of institutional capacity. The study contributes a cross-national, distribution-sensitive account of how fintech diffusion and institutions jointly shape private-sector credit, and it reframes the policy question around coordinated design, macroprudential supervision, and institutional resilience rather than the promotion of technology alone.

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References

- Demirgüç-Kunt, A.; Klapper, L.; Singer, D.; Ansar, S. *The Global Findex Database 2021*; The World Bank: Washington, DC, USA, 2022; ISBN 978-1-4648-1897-4.
- Klapper, L. *Expanding Financial Inclusion Through Digital Financial Services: A Literature Review*; World Bank: Washington, DC, USA, 2024.
- Mandić, A.; Marković, B.; Žigo, I.R. Risks of the Use of FinTech in the Financial Inclusion of the Population: A Systematic Review of the Literature. *J. Risk Financ. Manag.* **2025**, *18*, 250. <https://doi.org/10.3390/jrfm18050250>.
- OECD. *Supporting Informed and Safe Use of Short-Term Online Credit and Buy Now Pay Later Through Digital Financial Literacy*; OECD: Paris, France, 2025.
- Geels, F.W. Technological Transitions as Evolutionary Reconfiguration Processes: A Multi-Level Perspective and a Case-Study. *Res. Policy* **2002**, *31*, 1257–1274. [https://doi.org/10.1016/S0048-7333\(02\)00062-8](https://doi.org/10.1016/S0048-7333(02)00062-8).
- Wafi, I.; Pamuji, S.; Nasir, M.D.A. Financial Technology as a Socio-Technical Entity in the Digital Financial System: A Systematic Literature Review. *Indones. J. Innov. Multidiscipliner Res.* **2026**, *4*, 1–14. <https://doi.org/10.69693/ijim.v4i2.448>.
- Al-Qudah, A.A.; Al-Okaily, M.; Shiyyab, F.S.; Taha, A.A.D.; Almajali, D.A.; Masa'deh, R.; Warrad, L.H. Determinants of Digital Payment Adoption Among Generation Z: An Empirical Study. *J. Risk Financ. Manag.* **2024**, *17*, 521. <https://doi.org/10.3390/jrfm17110521>.
- Qatawneh, N.; Al-Okaily, A.; Al-Okaily, M.; Ur Rehman, S. Exploring the Antecedent Factors of Continuous Intention to Use Mobile Money: Insights from Emerging Markets. *Digit. Policy Regul. Gov.* **2025**, *27*, 175–200. <https://doi.org/10.1108/DPRG-04-2024-0080>.
- Berg, T.; Burg, V.; Gombović, A.; Puri, M. On the Rise of FinTechs: Credit Scoring Using Digital Footprints. *Rev. Financ. Stud.* **2020**, *33*, 2845–2897. <https://doi.org/10.1093/rfs/hhz099>.

10. Gomber, P.; Kauffman, R.J.; Parker, C.; Weber, B.W. On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *J. Manag. Inf. Syst.* **2018**, *35*, 220–265. <https://doi.org/10.1080/07421222.2018.1440766>.
11. Cornelli, G.; Gambacorta, L.; Pancotto, L. Buy Now, Pay Later: A Cross-Country Analysis. *BIS Q. Rev.* **2023**, December, 61–75. Available online: https://www.bis.org/publ/qtrpdf/r_qt2312.htm (accessed on 2 May 2026).
12. Cornelli, G.; Frost, J.; Gambacorta, L.; Rau, P.R.; Wardrop, R.; Ziegler, T. Fintech and Big Tech Credit: Drivers of the Growth of Digital Lending. *J. Bank. Financ.* **2023**, *148*, 106742. <https://doi.org/10.1016/j.jbankfin.2022.106742>.
13. Hou, J.; Zhang, Y. Digital Inclusive Finance Penetration and Household Debt Maturity Structure: Empirical Estimation Based on China Family Panel Studies Data. *PLoS ONE* **2025**, *20*, e0320080. <https://doi.org/10.1371/journal.pone.0320080>.
14. Liu, J.; Chen, Y.; Chen, X.; Chen, B. Digital Financial Inclusion and Household Financial Vulnerability: An Empirical Analysis of Rural and Urban Disparities in China. *Heliyon* **2024**, *10*, e35540. <https://doi.org/10.1016/j.heliyon.2024.e35540>.
15. Chai, S.; Qi, H. Mobile Payments and Households' Over-Indebtedness: Micro Evidence Based on Subjective and Objective Perspectives. *Sage Open* **2025**, *15*, 21582440251388078. <https://doi.org/10.1177/21582440251388078>.
16. Margan, S.K. The Pacing Problem Unplugged Part 1. *Contingencies*. 2025. Available online: <https://actuary.org/article/the-pacing-problem-unplugged-part-1/> (accessed on 10 June 2026).
17. Al-Okaily, M.; Abd Rahman, M.S.; Ali, A.; Abu-Shanab, E.; Masa'deh, R. An Empirical Investigation on Acceptance of Mobile Payment System Services in Jordan: Extending UTAUT2 Model with Security and Privacy. *Int. J. Bus. Inf. Syst.* **2023**, *42*, 123. <https://doi.org/10.1504/IJBIS.2023.128306>.
18. Das, A.R.; Chakraborty, A.; Goyal, N.; Roy, P. Financial Technology in Transition: Trends, Development, and Ways Forward. *J. Econ. Surv.* **2026**, *40*, 839–860. <https://doi.org/10.1111/joes.70029>.
19. Di Maggio, M.; Williams, E.; Katz, J. *Buy Now, Pay Later Credit: User Characteristics and Effects on Spending Patterns*; National Bureau of Economic Research: Cambridge, MA, USA, 2022.
20. Relja, R.; Ward, P.; Lifan Zhao, A. The Buy-Now-Pay-Later Ecosystem New (Algo)Rhythms of Spending and Reframed Relationships. In *Digital Project Practice for Banking and FinTech*; Auerbach Publications: Boca Raton, FL, USA, 2024; pp. 121–134.
21. Bazley, W.; Jannati, S. The influence of regional sentiment on online borrowing. *Int. Rev. Financ. Anal.* **2024**, *95*, 103423. <https://doi.org/10.1016/j.irfa.2024.103423>.
22. Berg, T.; Fuster, A.; Puri, M. FinTech Lending. *Annu. Rev. Financ. Econ.* **2022**, *14*, 187–207. <https://doi.org/10.1146/annurev-financial-101521-112042>.
23. AlSuwaidi, R.A.; Mertzanis, C. Financial Literacy and FinTech Market Growth around the World. *Int. Rev. Financ. Anal.* **2024**, *95*, 103481. <https://doi.org/10.1016/j.irfa.2024.103481>.
24. Xu, F.; Zhang, L. The Impact of Digital Payments on the Financial Vulnerability of Rural Households: Empirical Evidence from China. *Front. Sustain. Food Syst.* **2025**, *9*, 1553237. <https://doi.org/10.3389/fsufs.2025.1553237>.
25. Le, T.D. A Shift towards Household Lending during the Fintech Era: The Role of Financial Literacy and Credit Information Sharing. *Asia-Pac. J. Bus. Adm.* **2023**, *15*, 466–485. <https://doi.org/10.1108/APJBA-07-2021-0325>.
26. Murinde, V.; Petropoulou, A. How Is FinTech Shaping Household Portfolio Behaviour? *Int. J. Financ. Econ.* **2026**, Online First, 1–22. <https://doi.org/10.1002/ijfe.70218>.
27. Yuan, G.; Fang, J.; Sun, Y. The Impact of Fintech on the Nexus between Household Debt and Financial Crises: A Global Perspective. *Econ. Model.* **2024**, *130*, 106589. <https://doi.org/10.1016/j.econmod.2023.106589>.
28. Sikalao-Lekobane, O.L. Does FinTech Credit Enhance or Disrupt Financial Stability? *Int. Rev. Econ. Financ.* **2024**, *96*, 103489. <https://doi.org/10.1016/j.iref.2024.103489>.
29. Hodula, M. Does Fintech Credit Substitute for Traditional Credit? Evidence from 78 Countries. *Financ. Res. Lett.* **2022**, *46*, 102469. <https://doi.org/10.1016/j.frl.2021.102469>.
30. Li, R.; He, J. FinTech Development and Household Resilience to Negative Income Shocks: The Role of Informal Risk Sharing. *Int. Rev. Econ. Financ.* **2024**, *94*, 103401. <https://doi.org/10.1016/j.iref.2024.103401>.
31. Álvarez-Espino, M.; Fernández-López, S.; Rey-Ares, L.; Rodríguez-Gulías, M.J. Digital Financial Inclusion and Financial Vulnerability: An Exploratory Analysis of Spanish Households. *J. Risk Financ. Manag.* **2026**, *19*, 175. <https://doi.org/10.3390/jrfm19030175>.
32. Siddik, M.N.A.; Habibullah, M.S.; Kabiraj, S.; Rakib, S.H. Does Digital Finance Foster Financial Stability? Empirical Evidence from Cross-Country Analysis. *Economies* **2026**, *14*, 72. <https://doi.org/10.3390/economies14030072>.
33. Yang, J.; Wu, Y.; Huang, B. Digital Finance and Financial Literacy: Evidence from Chinese Households. *J. Bank. Financ.* **2023**, *156*, 107005. <https://doi.org/10.1016/j.jbankfin.2023.107005>.

34. Vik, P.M.; Kamerāde, D.; Dayson, K.T. The Link Between Digital Skills and Financial Inclusion—Evidence from Consumers Survey Data from Low-Income Areas. *J. Consum. Policy* **2024**, *47*, 373–393. <https://doi.org/10.1007/s10603-024-09567-w>.
35. Mushtaq, R.; Murtaza, G.; Yahiaoui, D.; Alessio, I.; Talpur, Q. Impact of Financial Literacy on Financial Inclusion and Household Financial Decisions: Exploring the Role of ICTs. *Int. Stud. Manag. Organ.* **2024**, *54*, 68–84. <https://doi.org/10.1080/00208825.2023.2281207>.
36. Liu, T.; Fan, M.; Li, Y.; Yue, P. Financial Literacy and Household Financial Resilience. *Financ. Res. Lett.* **2024**, *63*, 105378. <https://doi.org/10.1016/j.frl.2024.105378>.
37. Golpet, M.K.; Makoni, P.L.; Marozva, G. A Cointegrating Linkage of Financial Inclusion, Institutional Quality and Economic Growth in Sub-Saharan African Countries. *Int. J. Financ. Stud.* **2026**, *14*, 71. <https://doi.org/10.3390/ijfs14030071>.
38. Meniago, C. Digital Financial Inclusion and Economic Growth: The Moderating Role of Institutions in SADC Countries. *Int. J. Financ. Stud.* **2025**, *13*, 4. <https://doi.org/10.3390/ijfs13010004>.
39. Vijayagopal, P.; Jain, B.; Ayinippully Viswanathan, S. Regulations and Fintech: A Comparative Study of the Developed and Developing Countries. *J. Risk Financ. Manag.* **2024**, *17*, 324. <https://doi.org/10.3390/jrfm17080324>.
40. Tutar, H.; Tutar, S.; Medetoglu, B.; Kalayci, M. From Risk to Responsibility: Examining the Financial Resilience of Banks. *Manag. Decis.* **2025**, *63*, 2061–2086. <https://doi.org/10.1108/MD-10-2023-2017>.
41. Tutar, H.; Akçi, Y.; Fialova, V.; György, K. The Asymmetric Impact of Digital Infrastructure on Income Inequality: A Panel Quantile Regression Analysis of OECD Countries. *Econ. Sociol.* **2025**, *18*, 208. <https://doi.org/10.14254/2071-789X.2025/18-4/10>.
42. Chikeya, C.K.; Ntsalaze, L. Determinants of Household Debt: A Systematic Review of the Literature. *Economies* **2025**, *13*, 76. <https://doi.org/10.3390/economies13030076>.
43. Vijverberg, C.-P.C. Income Inequality and Household Debt: A U.S. State-Level Spatial Analysis. *Econ. Model.* **2024**, *138*, 106772. <https://doi.org/10.1016/j.econmod.2024.106772>.
44. International Council on Systems Engineering. *A Complexity Primer for Systems Engineers*; International Council on Systems Engineering: San Diego, CA, USA, 2015.
45. Bar-Yam, Y. From Big Data to Important Information. *Complexity* **2016**, *21*, 73–98. <https://doi.org/10.1002/cplx.21785>.
46. Geels, F.W.; Kern, F.; Fuchs, G.; Hinderer, N.; Kungl, G.; Mylan, J.; Neukirch, M.; Wassermann, S. The Enactment of Socio-Technical Transition Pathways: A Reformulated Typology and a Comparative Multi-Level Analysis of the German and UK Low-Carbon Electricity Transitions (1990–2014). *Res. Policy* **2016**, *45*, 896–913. <https://doi.org/10.1016/j.respol.2016.01.015>.
47. Eberhardt, M.; Teal, F. Econometrics for Grumblers: A New Look at the Literature on Cross-Country Growth Empirics. *J. Econ. Surv.* **2011**, *25*, 109–155. <https://doi.org/10.1111/j.1467-6419.2010.00624.x>.
48. Pesaran, M.H.; Yamagata, T. Testing Slope Homogeneity in Large Panels. *J. Econom.* **2008**, *142*, 50–93. <https://doi.org/10.1016/j.jeconom.2007.05.010>.
49. Hayman, G.; Pang, R.K.-K. *Reframing Financial Markets as Complex Systems: Tools for Systemic Risk Analysis, Portfolio Management, and System-Level Investing*; CFA Institute: Charlottesville, VA, USA, 2025.
50. Holland, J.H. *Signals and Boundaries: Building Blocks for Complex Adaptive Systems*; The MIT Press: Cambridge, MA, USA, 2012; ISBN 9780262305891.
51. Wang, J. Sociotechnical Enveloping: Productization of APIs and the Transnational Expansion of Alipay+. *Platf. Soc.* **2025**, *2*, 29768624251377198. <https://doi.org/10.1177/29768624251377198>.
52. Pesaran, M.H. General Diagnostic Tests for Cross-Sectional Dependence in Panels. *Empir. Econ.* **2021**, *60*, 13–50. <https://doi.org/10.1007/s00181-020-01875-7>.
53. Pesaran, M.H. A Simple Panel Unit Root Test in the Presence of Cross-section Dependence. *J. Appl. Econom.* **2007**, *22*, 265–312. <https://doi.org/10.1002/jae.951>.
54. Driscoll, J.C.; Kraay, A.C. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Rev. Econ. Stat.* **1998**, *80*, 549–560. <https://doi.org/10.1162/003465398557825>.
55. Canay, I.A. A Simple Approach to Quantile Regression for Panel Data. *Econom. J.* **2011**, *14*, 368–386. <https://doi.org/10.1111/j.1368-423X.2011.00349.x>.
56. Galvao, A.F. Quantile Regression for Dynamic Panel Data with Fixed Effects. *J. Econom.* **2011**, *164*, 142–157. <https://doi.org/10.1016/j.jeconom.2011.02.016>.
57. Dumitrescu, E.-I.; Hurlin, C. Testing for Granger Non-Causality in Heterogeneous Panels. *Econ. Model.* **2012**, *29*, 1450–1460. <https://doi.org/10.1016/j.econmod.2012.02.014>.
58. Nguyen, L.; Tran, S.; Ho, T. Fintech Credit, Bank Regulations and Bank Performance: A Cross-Country Analysis. *Asia-Pac. J. Bus. Adm.* **2022**, *14*, 445–466. <https://doi.org/10.1108/APJBA-05-2021-0196>.

59. Qi, H.; Yang, K.; Wu, R.; Wu, X.; Wang, G.; Zhang, Z. Bank FinTech and Credit Risk-Taking: The Role of Competition and Regulation. *Risk Manag.* **2026**, *28*, 30. <https://doi.org/10.1057/s41283-026-00212-z>.
60. Hodula, M. Interest Rates as a Finance Battleground? The Rise of Fintech and Big Tech Credit Providers and Bank Interest Margin. *Financ. Res. Lett.* **2023**, *53*, 103685. <https://doi.org/10.1016/j.frl.2023.103685>.
61. Cuadros-Solas, P.J.; Cubillas, E.; Salvador, C.; Suárez, N. Digital Disruptors at the Gate. Does FinTech Lending Affect Bank Market Power and Stability? *J. Int. Financ. Mark. Inst. Money* **2024**, *92*, 101964. <https://doi.org/10.1016/j.intfin.2024.101964>.
62. Verma, R.; Chatterjee, D. Relative Impact of Digital and Traditional Financial Inclusion on Financial Resilience: Evidence from 13 Emerging Countries. *J. Econ. Bus.* **2025**, *133*, 106233. <https://doi.org/10.1016/j.jeconbus.2025.106233>.
63. Kass-Hanna, J.; Lyons, A.C.; Liu, F. Building Financial Resilience through Financial and Digital Literacy in South Asia and Sub-Saharan Africa. *Emerg. Mark. Rev.* **2022**, *51*, 100846. <https://doi.org/10.1016/j.ememar.2021.100846>.
64. Górka, J. The Rise of Instant Payments: A Cross-Country Comparison. *Cent. Eur. Manag. J.* **2025**, *33*, 575–589. <https://doi.org/10.1108/CEMJ-10-2024-0297>.

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