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Digital Financial Ecosystems and Trade-Related Working Capital Finance: Firm-Level Evidence from 39 Economies

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Abstract

How firms finance purchases and inventories may depend increasingly on the digital financial environment in which they operate, but cross-economy evidence on trade credit and customer advances remains limited. We merge firm-level Enterprise Survey records with digital finance, insurance, digital infrastructure, and macroeconomic indicators. The complete-case sample comprises 32,049 firms across 39 economies surveyed during 2014–2020. Conventional digital finance and insurance capacity are positively associated with percentage, fractional share, and adoption outcomes across OLS, fractional logit, and logit specifications. The interaction between mobile money and digital infrastructure is negative but only marginally significant for adoption, supporting a diminishing adoption association at the 10% level; it is nonsignificant for percentage and fractional outcomes and is absent among existing users. Nonlife digital readiness negatively moderates the fractional share at the 5% level and adoption at the 10% level, but not the OLS percentage outcome. Alternative received and granted trade credit outcomes yield positive interaction signs, indicating that the estimated relationships are sensitive to the specific working capital outcome examined. Overall, the findings support a disaggregated ecosystem perspective but remain associational because national exposures are not randomly assigned and the data are repeated across sections.

Keywords: digital finance; mobile money; insurance capacity; supplier credit; customer advances; working capital; digital infrastructure; two-part model

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1. Introduction

Supplier credit and customer advances form part of the operating cycle because they link purchases, production, sales, and settlement when bank liquidity is expensive or unavailable. As a result, they do more than substitute bank loans. Trade credit conditions are partly determined by product characteristics; interfirm credit can help to maintain supply relations in the aftermath of business shocks (Giannetti et al., 2011; Ersahin et al., 2024). Conversely, late payments, buyer defaults, and shifts in bargaining power may shift financial pressure from one company to another in the supply chain (Beyer & Herzog, 2021; Yang et al., 2021).

Digital financial development can transform the practical arrangements in which operational finance is used. Mobile money and digital payments can reduce transfer frictions and create transaction records, while financial institution accounts and debit cards expand the channels through which obligations can be settled (Aron, 2018; Ozili, 2018). Recent

studies associate digital transaction capability with interfirm credit relationships, but their technologies, settings, and financing margins differ. Digital payment adoption among informal firms in Ghana is associated with both receiving and extending trade credit (Abdulai et al., 2024). Kenyan informal entrepreneurs using mobile money are more likely to transact on credit with suppliers and customers (Tetteh et al., 2025). Xu et al. (2025) associate city-level digital finance with longer trade credit recovery periods among Chinese-listed firms. Zhang et al. (2025) associate customer digitalization with lower reliance on supplier financing and greater credit provision to downstream customers.

The literature, therefore, contains both a common core and an unresolved boundary. The common core is that digital finance capability, financial development, and institutional conditions shape how firms' access, settle, or allocate financing; the disagreement concerns whether additional digital capacity complements relationship-based operating finance or reduces its relative role and whether the relevant margin is adoption, financing intensity, or the direction of trade credit flows. Cross-country studies show that digital credit depends on regulation, innovation capacity, and financial development, while trade credit evidence shows that local finance, enforcement, product characteristics, and contractual conditions can alter firms' use of operating credit (Le et al., 2023; Giannetti et al., 2011; Beyer & Herzog, 2021; Fasano et al., 2024). These differences matter because evidence from one technology or one side of a bilateral credit relationship cannot establish how several national financial system capabilities jointly relate to supplier credit/customer advances across economies. The unresolved question is thus not simply whether digital finance is beneficial but how distinct digital and institutional capabilities coexist, substitute, or complement one another across the adoption and intensity margins of trade-related working capital finance.

This study asks: How are national digital finance and insurance system capabilities associated with firms' use of supplier credit and customer advances for working capital, and when does digital readiness alter the mobile money association? We merge World Bank Enterprise Survey firm records with Global Findex, Global Financial Development Database, and World Development Indicators data. The complete-case sample contains 32,049 firms in 39 economies surveyed from 2014 through 2020. Percentage, fractional share, and adoption models are estimated with industry and survey year effects and country-clustered standard errors. The estimates are explicitly associational because the country-level exposures are not randomly assigned and the data are repeated cross-sections rather than a firm panel.

The study contributes in four linked ways. First, it separates conventional digital finance—digital payments, financial institution accounts, and debit card ownership—from mobile money, allowing different digital rails to have different associations with operating finance. Second, it brings national insurance capacity into the same framework as a risk-bearing and monitoring environment and evaluates a narrower nonlife digital readiness construct without treating it as observed firm-level InsurTech adoption (Eling & Lehmann, 2018; Stoeckli et al., 2018). Third, it separates adoption from conditional financing intensity through a two-part design, which is substantively important for an outcome with a large mass at zero (Belotti et al., 2015). Fourth, the empirical pattern is deliberately non-uniform: conventional digital finance and insurance capacity are positively associated with the main outcome across estimators, whereas the mobile money interactions are weaker, threshold-dependent, and sensitive to whether the outcome captures adoption, conditional intensity, or distinct received/granted trade credit flows. The theoretical value lies in identifying ecosystem boundary conditions rather than treating digital finance indicators as interchangeable; the practical value lies in showing why policy makers and firms should distinguish access to digital rails from the specific financing role those rails may support. All of these interpretations remain associational.

2. Literature Review and Theoretical Framework

2.1. Trade-Related Working Capital Finance

Trade credit embeds financing in a business transaction between companies. Previous research generally agrees that this form of finance is shaped by transaction characteristics and financial constraints, rather than by passive accounting. Product characteristics and buyer market power shape trade credit terms (Giannetti et al., 2011), while credit-rationed European SMEs were more likely to use trade credit during the financial crisis (Casey & O'Toole, 2014). At the same time, the literature does not indicate a single beneficial or liquidity effect: the same inter-financial arrangement may redistribute liquidity, risk, and bargaining exposure between purchasers and suppliers. This distinction is central to this study, as supplier credit and customer advances represent operational funding margins whose meaning depends on the role of the company in the transaction.

In this way, working capital finance related to trade can support production networks, but it can also transfer financial pressure through payment terms, buyer defaults, and contract structure (Ersahin et al., 2024; Beyer & Herzog, 2021). Trade credit insurance illustrates the same two-way logic: it can smooth the cash flows of suppliers and support the monitoring of buyer creditworthiness, but the allocation of these functions is contractual (Yang et al., 2021). This synthesis is, therefore, conditional rather than uniformly positive: operating credit can relax financing constraints or provide continuity, but its effects and determinants vary by counterparty and contractual setting. This in turn leads to the next question, which is whether digital finance capabilities change the transaction, information, and settlement environment in which these operating credit relationships are employed.

2.2. Digital Finance, Mobile Money, and Firms

Digital finance encompasses several digitally delivered financial services (Ozili, 2018). Kenyan household evidence links mobile money to lower transfer costs and remittance-based risk sharing (Jack & Suri, 2014); a longer-run study documents consumption and poverty improvements (Suri & Jack, 2016). Aron (2018) reviews these channels and their identification limits. For companies, similar channels may include faster settlement, easier transfer of liquidity, and digital transaction history. These mechanisms are naturally linked to interfirm finance but do not mean that all forms of digital finance should be linked to commercial working capital in the same way.

Firm-level evidence illustrates this limit. Islam et al. (2018) link mobile money use to fixed-asset investment among East African firms, whereas evidence for productivity and complementarity with formal finance is more contextual (Konte & Tetteh, 2023). More recent studies indicate that digital payments and mobile money are linked to receipt and extension of trade credit for informal firms (Abdulai et al., 2024; Tetteh et al., 2025). In a Chinese-listed firm setting, customer digitalization is associated with less financing from suppliers, but more credit supplied to downstream customers (Zhang et al., 2025). These differing financing margins motivate the unresolved question of whether traditional digital finance and mobile money act as a complement, substitute, or context-dependent channel, considering wider national financial and infrastructure conditions.

2.3. Insurance Capacity and Digital Infrastructure

At the contract level, trade credit insurance can smooth supplier cash flows and create buyer-monitoring incentives (Yang et al., 2021). Using national insurance capacity as a broader risk-bearing environment is this study's proposed cross-level extension, rather than a national effect established by that source. At the same time, digitalization is reshaping insurance value chains, customer interfaces, business processes, and data-based risk assessment (Eling & Lehmann, 2018; Stoeckli et al., 2018). The measure of insurance capacity

used here, therefore, represents the national financial system environment, rather than the adoption of a specific product in the field of Insurtech at the firm level. More generally, financial research shows that corporate financing decisions may be interdependent on company characteristics, macroeconomic conditions, and institutional environments; Botta and Colombo (2022) document these interactions in the capital structure dynamics. This evidence does not directly support supplier credit, customer advances, mobile money, or digital finance, but it supports a more limited institutional proposition that financial relations may be subject to a country-specific context.

The digital infrastructure adds a second layer of conditioning. Greater network coverage is associated with greater uptake of digital financial services, although the respective network technologies differ between mobile and bank-based systems (Mothobi & Kebotsamang, 2024). Aron (2018) discusses how mobile money can reduce transfer costs under inadequate transport infrastructure. Diffusion also depends on regulation and coordination among service providers and other actors (Lashitew et al., 2019). Insurance capacity and digital infrastructure are, therefore, not only additional predictors; they describe the institutional and technological conditions, which can change the relative usefulness of specific digital financial channels. This common logic of conditions is what motivates the ecosystem framework, rather than a series of disconnected arguments about direct effects.

2.4. Ecosystem Perspective

The ecosystem perspective provides an analytical bridge between these structures. Adner (2017) defines ecosystems around the convergence of interdependent activities needed to provide a focal value proposition, and Jacobides et al. (2018) emphasize the modularity and complementarity of the ecosystem players. Neither study tests the financial relationships examined here; their role is more limited: they provide a framework for asking when different competences become complementary, interchangeable, or jointly indispensable. Applied to working capital finance related to trade, the focal point of the proposal is the ability to sustain purchases, inventories, and settlement by means of supplier credit or customer advances. Conventional digital finance provides formal payment and account channels; mobile money provides a mobile-based transfer channel; insurance provides risk-bearing and monitoring capacity at the system level; and digital infrastructure supports connectivity, exchange of information, and provision of services.

This mapping also clarifies the logic of complementarity and substitution. Conventional digital finance and insurance capabilities can complement operational finance by improving settlement, documentation, monitoring, and risk-taking. Mobile money can also complement these functions by adding a separate transfer path. However, as infrastructure and formal financial capabilities become more widespread, mobile money may become less distinct as alternative channels carry out overlapping settlement and information functions. The theory of ecosystems is used only to organize this interdependence; the direction of financial associations is based on the evidence on finance and digital finance developed in the hypothesis section.

Finally, the framework distinguishes between two ranges of the focal point of the offer. Adoption asks whether the company has gone from zero to using supplier credit or customer advances; conditionality asks how much working capital is allocated through this channel after use. The same ecosystem capacity may facilitate entry, but it is of little relevance to the amount allocated after entry, when commercial conditions, bargaining power, and counterparty risk become more important. The resulting logical thread is therefore: operational finance → national financial ecosystem → institutional and digital capabilities → complementarity or substitution → adoption versus financing intensity. Section 3 translates this framework into hypothesis-specific predictions.

3. Hypothesis Development

3.1. Conventional Digital Finance and Trade-Related Working Capital Finance

Conventional digital finance development here includes use of digital payments alongside accounts at financial institutions and debit cards, which may lower the physical effort of initiating, recording, and settling transactions, as well as making payment commitments more easily documented. It may also expand access and lower transaction frictions, while creating stability and governance risks that arise when institutional safeguards fail to catch up with adoption (Ozili, 2018). For buyer–supplier relationships, improved settlement channels and records should help administer deferred payment and customer advances.

The predicted association is consistent with emerging evidence at both informal firm and corporate levels. Digital payment adoption is associated with firms' demand for and supply of trade credit in Ghana, with transaction efficiency, security, and trust offered as mechanisms (Abdulai et al., 2024). Xu et al. (2025) associate city-level digital finance with longer trade credit recovery periods among Chinese-listed firms. Zhang et al. (2025) find lower reliance on supplier financing but greater credit provision to downstream customers after customer digitalization. These studies do not identify the same national model used in this context but support the view that the ability to transact digitally is important for interfirm financing.

In this context, conventional digital finance is expected to complement and not replace relationship-based operating loans. Accounts, cards, and digital payments provide formal settlement and record-keeping capabilities, while supplier credit and customer advances address timing mismatches in the context of inventories and sales. The ecosystem mechanism is a complementarity between the settlement layer and the operating financial layer: stronger formal digital channels can facilitate the execution and documentation of inter-firm commitments without replacing the underlying buyer–seller financial relationship. Evidence that mobile money can be more productive when combined with traditional finance is consistent with the broader importance of complementary financial capabilities (Konte & Tetteh, 2023). The prediction is, therefore, a positive association at the national environment level; it does not imply that country-level digital finance causes any individual firm to borrow more.

Hypothesis 1 (H1). *Conventional digital finance development is positively associated with firms' use of supplier credit/customer advances for working capital.*

3.2. Insurance Capacity and Trade-Related Working Capital Finance

The insurance capacity reflects the size of nonlife insurance premiums and insurance assets relative to the economy. The proposed mechanism is greater capacity to price risk, pool losses, monitor counterparties, and support financial contracts. Trade credit insurance research supplies a narrower contract-level example of cash flow smoothing and buyer-monitoring incentives (Yang et al., 2021); the national capacity interpretation here remains an extension proposed by this study. These characteristics at the level of the system may be relevant for the operation of credit even if the individual undertaking surveyed does not purchase commercial credit insurance, as suppliers, customers, banks, logistic providers, and insurers are all operating in the same business environment.

One concrete example of this channel is trade credit insurance. Depending on the design of the contract, this may both smooth the cash flow of the supplier and create incentives to monitor the continued creditworthiness of the buyer (Yang et al., 2021). At the same time, digitization is changing the value chains of insurance, service interfaces, business processes, and data-based risk assessment (Eling & Lehmann, 2018). Insurtech

innovation can, therefore, change the way value is generated in the insurance system, rather than simply automating the current product (see Stoeckli et al., 2018).

The theoretical mechanism for the insurance hypothesis is the complementarity of institutions. Supplier credit and customer advances expose counterparties to payment and default risks; a more insurance-based national environment can coexist with more risk pooling, monitoring, and contracting capacity that supports these relationships. Trade credit insurance offers a concrete illustration of the monitoring and cash flow smoothing functions that can arise around interfirm credit (Yang et al., 2021), but the present construct is deliberately broader than firm-level trade credit insurance use. The hypothesis, therefore, concerns the association between an ecosystem-level risk-bearing environment and trade-related working capital finance, not the causal effect of any specific insurance product or InsurTech application.

Hypothesis 2 (H2). *National insurance capacity is positively associated with firms' use of supplier credit/customer advances for working capital.*

3.3. Digital Infrastructure as a Moderator of Mobile Money

Mobile money may serve as a bridge where bank branches, fixed broadband, secure servers, or conventional payment instruments are limited. Its attractiveness is partly due to the conversion of widespread mobile access into direct transfer and storage functions; empirical evidence links the spread of mobile money to lower transaction costs and better risk-sharing (Jack & Suri, 2014; Aron, 2018). A similar mechanism can work for businesses by making payments to suppliers and collecting revenues from customers, and recent Kenyan evidence shows that mobile money entrepreneurs are more likely to make credit transactions with both groups (Tetteh et al., 2025).

There is a reciprocal relationship with infrastructure. Adoption of digital financial services can be aided by increased network coverage, particularly in situations where dependable connectivity is necessary for delivery (Mothobi & Kebotsamang, 2024). Aron (2018) discusses the potential transfer cost advantage of mobile money where transport infrastructure and conventional banking access are limited. Infrastructure by itself does not determine use because diffusion still depends on lead firms, regulations, and other complementary actors (Lashitew et al., 2019).

The moderation prediction follows from substitution within the ecosystem. As internet use, secure server density, broadband, and mobile subscriptions rise together, firms have more channels for payments, information exchange, and formal finance. Mobile money may then become less distinctive as an entry route into supplier credit/customer advances even if infrastructure raises the overall level of digital activity. The proposed substitution mechanism draws on the discussion of transfer cost reductions under inadequate transport infrastructure (Aron, 2018), while network coverage itself supports digital finance adoption (Mothobi & Kebotsamang, 2024). Neither source tests the present interaction hypothesis. The hypothesis, therefore, concerns the slope of the mobile money association across infrastructure conditions, not a claim that infrastructure is intrinsically harmful to trade-related finance.

Hypothesis 3 (H3). *Digital infrastructure negatively moderates the association between mobile money and firms' use of supplier credit/customer advances for working capital.*

3.4. Adoption Versus Conditional Financing Intensity

The dependent variable has a large mass at zero because many firms do not use supplier credit or customer advances at all. A single mean model can conceal two decisions: whether

to adopt the financing channel and, conditional on adoption, what share of working capital to fund through it. Two-part models explicitly separate a binary first part from a positive-outcome second part and are designed for mixed discrete–continuous outcomes (Belotti et al., 2015). Here, that distinction matters substantively as well as statistically.

The distinction between adoption and intensity is also implied by the framework. Infrastructure and mobile money have a combined influence on whether the basic transfer, communication, and authentication capabilities are sufficient for a company to enter an operating credit relationship. However, the share of funding may be more heavily dependent upon the size of orders, production cycles, bargaining power, product characteristics, and counterparty risk (Giannetti et al., 2011). Trade credit insurance design likewise indicates that monitoring and operational decisions remain relevant after a credit relationship exists (Yang et al., 2021). The theoretical prediction is, therefore, a boundary condition: the mobile money–infrastructure substitution should be more visible at adoption than at conditional intensity.

The mixed firm-level evidence on mobile money is also consistent with the adoption argument, as mobile money use is associated with fixed asset investment among East African firms, but mobile money has no robust direct association with productivity, while its combination with bank capital and, to some extent, bank accounts can improve productivity (Islam et al., 2018; Konte & Tetteh, 2023). This pattern is consistent with mobile money assisting firms in entering or connecting to a financing channel without necessarily deciding the amount utilized post-entry. This is still a descriptive comparison, though, as we did not formally test the equivalence of coefficients across the two nonlinear samples.

Hypothesis 4 (H4). *The negative moderation predicted in H3 is expected to be concentrated primarily in the adoption of supplier credit/customer advances rather than in financing intensity among firms already using the channel.*

3.5. Nonlife Digital Readiness as an Alternative Moderator

The nonlife digital readiness measure is the geometric mean of normalized nonlife-insurance penetration and digital infrastructure. Because of this, a zero value in either normalized component sets the composite to zero, while a low value in either component constrains the composite even when the other is high. The geometric mean construction is specific to this study. Ecosystem theory provides conceptual motivation through alignment and complementarity among activities and actors (Adner, 2017; Jacobides et al., 2018); neither source proposes this index.

When nonlife insurance and digital infrastructure are both relatively mature, the environment can support data-intensive underwriting, risk monitoring, and several formal payment and financing channels. Research on digital insurance documents changes in value chain activities, customer interfaces, business processes, data-based risk assessment, and innovation capabilities (Eling & Lehmann, 2018; Stoeckli et al., 2018). These developments may complement mobile money, but they can also make it less distinctive by providing alternative routes for settlement, verification, and risk allocation.

The alternative readiness hypothesis extends the same substitution logic to a joint institutional–digital capability. When nonlife insurance penetration and digital infrastructure are both relatively weak, mobile money may have a more distinctive role in enabling operating credit relationships. As both capabilities mature, firms operate in an environment with more formal routes for settlement, information, and risk allocation, potentially reducing the relative association of mobile money with the focal working capital channel. Because the readiness index combines insurance penetration with infrastructure rather than the broader insurance capacity PCA, this is a narrower alternative boundary condition

test rather than a reformulation of the preceding hypotheses. The directional prediction is retained because it follows from the pre-specified substitution mechanism, not from the observed coefficient.

Hypothesis 5 (H5). *Nonlife digital readiness negatively moderates the association between mobile money and firms' use of supplier credit/customer advances for working capital.*

4. Materials and Methods

4.1. Research Design and Data Sources

The study uses an observational, firm-level repeated cross-section. The data contains 191,030 firm survey observations from 172 economies over 2014–2025. Firm outcomes and controls originate in the World Bank Enterprise Surveys (WBESs); national digital finance indicators come from Global Findex; insurance indicators come from the Global Financial Development Database (GFDD); and infrastructure and macroeconomic variables come from World Development Indicators (WDIs). The Global Findex source report describes the measurement framework for account ownership, payment use, and mobile money (Demirgüç-Kunt et al., 2018).

The unit of observation is one WBES firm survey record identified by idstd. The data are not a firm panel. Country-level exposures are repeated across firms within the relevant economy and survey year. Findex 2014 values are assigned to WBESs conducted in 2014–2016, and Findex 2017 values are assigned to surveys conducted in 2017–2020; GFDD and WDI variables are matched by economy and year. The complete-case sample thus contains 32,049 firms, 39 economies (Appendix A), 39 economy-year cells, and 42 observed ISIC Revision 4 industries. Although the database covers the period until 2025, the estimation sample covers the period 2014–2020 as the later observations do not contain full insurance capacity data according to the locked sample rule.

4.2. Sample Construction

Table 1 shows the order of sample cascades. No missing values shall be attributed, no observations shall be weighted, and the final models shall not be weighted. The principal reduction occurs when the insurance capacity requirement is applied: 86,390 observations with valid outcomes, controls, macro-variables, and Findex measures fall to 32,049 complete observations. This restriction defines the final sample used by the executed analysis; it is not altered to improve statistical significance.

Table 1. Sequential construction of the final analytical sample.

Restriction Stage	Observations	Coverage or Criterion
Initial data	191,030	172 economies; 2014–2025
Valid main outcome	183,946	Nonmissing supplier credit/customer advances percentage
Firm controls complete	177,543	All locked firm controls present
Macroeconomic controls complete	146,059	All locked WDI macro-controls present
Findex measures complete	86,390	Conventional digital finance and mobile money present
Insurance capacity complete	32,049	Final complete-case sample
Digital infrastructure complete	32,049	No further loss

Notes: Counts are sequential. The final sample contains 32,049 firms in 39 economies and covers survey years 2014–2020.

4.3. Variables and Index Construction

The principal dependent variable is the percentage of working capital financed through purchases on credit from suppliers and advances from customers (WBES item k3f), denoted trade_wc_pct. The fractional outcome is trade_wc_share = trade_wc_pct/100. The adoption outcome, trade_wc_use, equals one when trade_wc_pct is greater than zero and zero otherwise. Robustness outcomes use the shares of trade credit received (WBES k1c) and granted (WBES k2c).

Conventional digital finance is the standardized first principal component of digital payment use, financial institution account ownership, and debit card ownership. PCA reduces correlated indicators into orthogonal components that successively maximize explained variance (Jolliffe & Cadima, 2016). The first component is estimated on 122 distinct economy–Findex-wave cells, explains 84.70% of component variance, and has eigenvector weights of 0.538, 0.596, and 0.596. Mobile money is the standardized value of the single mobile money account indicator; it is not a PCA index.

Insurance capacity is the standardized principal component of nonlife insurance premiums/GDP and insurance company assets/GDP. Estimated on 76 distinct economy-year cells, its first component explains 76.13% of variance and assigns equal eigenvector weights of 0.707 to the two inputs. Digital infrastructure is the standardized first principal component of internet users, log(1 + secure servers), fixed broadband subscriptions, and mobile cellular subscriptions. Estimated on 191 economy-year cells, it explains 77.23% of variance, with eigenvector weights of 0.528, 0.538, 0.517, and 0.405.

For the alternative readiness measure, nonlife penetration and digital infrastructure are separately min–max-normalized to [0,1]. Their geometric mean is nonlife_digital_readiness_01 = sqrt(nonlife_penetration_01 × digital_infrastructure_01), which is then standardized. A broader InsurTech readiness robustness measure analogously combines min–max-normalized insurance capacity and infrastructure before standardization. The geometric mean makes the composite low when either constituent capability is low. Table 2 records every operational definition and transformation used in the final models.

Table 2. Variables, source indicators, and transformations.

Construct	Analysis Variable	Source or Components	Transformation
Working capital finance (%)	trade_wc_pct	WBES k3f; percentage financed by supplier credit/customer advances	None
Working capital share	trade_wc_share	Bounded fractional outcome	trade_wc_pct/100
Adoption	trade_wc_use	Any use of the channel	1[trade_wc_pct > 0]
Conventional digital finance	ft_conventional_z	Digital payments; financial institution account; debit card	PC1, then standardized
Mobile money	ft_mobile_z	Mobile money account indicator	Standardized single indicator; not PCA
Insurance capacity	insurance_capacity_z	Nonlife premiums/GDP; insurer assets/GDP	PC1, then standardized
Digital infrastructure	digital_infrastructure_z	Internet users; log-secure servers; fixed broadband; mobile subscriptions	PC1, then standardized
InsurTech readiness (robustness)	insurtech_readiness_z	Insurance capacity and digital infrastructure	Min–max each; geometric mean; standardized
Nonlife digital readiness	nonlife_digital_readiness_z	Nonlife penetration and digital infrastructure	Min–max each; geometric mean; standardized

Table 2. *Cont.*

Construct	Analysis Variable	Source or Components	Transformation
Firm size	ln_employees	Permanent full-time employees	Natural log
Firm age	ln_firm_age	Survey year minus establishment year	ln(1 + age)
Exporter	exporter	Positive direct or indirect exports	Binary indicator
Foreign ownership	foreign_ownership_pct	Foreign private ownership	Percentage
External audit	external_audit	Externally audited financial statements	Binary indicator
Real GDP per capita	ln_gdp_per_capita	WDI NY.GDP.PCAP.KD	Natural log
GDP growth	macro_gdp_growth	WDI NY.GDP.MKTP.KD.ZG	Annual percentage
Inflation	macro_inflation	WDI FP.CPI.TOTL.ZG	Annual percentage
Private credit	macro_private_credit	WDI FS.AST.PRVT.GD.ZS	Percentage of GDP

Notes: PCA = principal component analysis; WBESs = World Bank Enterprise Surveys; WDIs = World Development Indicators. Findex codes are g20.any, mobileaccount.t.d, fiaccount.t.d, and fin2.t.a. GFDD indicators use codes GFDD.DI.10 and GFDD.DI.11. Infrastructure WDI codes are IT.NET.USER.ZS, IT.NET.SECR.P6, IT.NET.BBND.P2, and IT.CEL.SETS.P2.

4.4. Control Variables

Controls at the enterprise level include the natural log of full-time employees, the natural log of one plus enterprise age, the indicator of the exporter, the percentage of foreign private ownership, and the indicator of the external audit. Macroeconomic checks include the natural log of real GDP per capita, annual real GDP growth, annual inflation in consumer prices, and domestic credit to the private sector (% of GDP). Each model includes indicators for industry and survey year. Openness of trade is available in the database but is excluded from the locked final specification.

4.5. Estimation Strategy

The executed analyses used Stata 15.0. H1 and H2 are assessed jointly using three dependent variable specifications. OLS is used for the percentage outcome, fractional logit for the bounded share, and binary logit for adoption. Equation (1) presents the common linear index, with i denoting firms, c economies, t survey years, and s industries. CDF denotes conventional digital finance, MM is mobile money, IC is insurance capacity, X is the vector of controls, and δ_s and τ_t are industry and survey year effects. For the nonlinear specifications, the reported coefficients are parameters on the logit link index and are not percentage point marginal effects; marginal effects are reported separately where they were calculated.

For the fractional and adoption models, the conditional mean or probability is linked to the same index through the logistic function $\Lambda(\cdot)$, as shown in Equation (2). Fractional logit is appropriate because the dependent share includes both zero and one and does not require transforming boundary observations (Papke & Wooldridge, 1996). H1 corresponds to $\beta_1 > 0$ and H2 to $\beta_3 > 0$ across the three specifications.

H3 uses a separate specification containing MM, digital infrastructure (DI), $MM \times DI$, IC, the common controls, and industry and survey year effects, as shown in Equation (3); CDF is excluded. H4 uses the same variable set for its adoption and users-only intensity models. Because interaction coefficients in nonlinear models do not by themselves describe probability changes, the adoption model is followed by average marginal effects of mobile money at the 10th, 25th, 50th, 75th, and 90th percentiles of infrastructure. H4 compares the full-sample adoption logit with a conditional fractional logit among the 9078 positive users, consistent with the two-part distinction described by Belotti et al. (2015).

H5 is a separate alternative specification containing mobile money, nonlife digital readiness (NDR), their interaction, the common controls, and industry/year effects. It does not include conventional digital finance or the broader insurance capacity PCA. This precise specification is maintained to ensure consistency with empirical analysis and to avoid the presentation of a model which has not actually been estimated. The robustness tests replace the result with the trade credit received and the trade credit granted, while the alternative OLS model replaces the insurance capacity with a wider mix of InsurTech competencies.

$$WC_{ict} = \alpha + \beta_1 CDF_{ct} + \beta_2 MM_{ct} + \beta_3 IC_{ct} + \gamma' X_{ict} + \delta_s + \tau_t + \varepsilon_{ict} \quad (1)$$

$$\begin{aligned} \mathrm{E}(Share_{ict} \mid \text{covariates}) &= \Lambda(\alpha + \beta_1 CDF_{ct} + \beta_2 MM_{ct} + \beta_3 IC_{ct} + \gamma' X_{ict} + \delta_s + \tau_t) \\ \Pr(Use_{ict} = 1 \mid \text{covariates}) &= \Lambda(\alpha + \beta_1 CDF_{ct} + \beta_2 MM_{ct} + \beta_3 IC_{ct} + \gamma' X_{ict} + \delta_s + \tau_t) \end{aligned} \quad (2)$$

$$\begin{aligned} \eta_{\mathrm{H3},ict} &= \alpha + \beta_1 MM_{ct} + \beta_2 DI_{ct} + \beta_3 (MM_{ct} \times DI_{ct}) + \beta_4 IC_{ct} \\ &\quad + \gamma' X_{ict} + \delta_s + \tau_t \\ WC_{ict} &= \eta_{\mathrm{H3},ict} + \varepsilon_{ict} \ (\mathrm{OLS}); \ \mathrm{E}(Share_{ict} \mid \text{covariates}) = \Lambda(\eta_{\mathrm{H3},ict}) \ (\text{fractional logit}) \\ \Pr(Use_{ict} &= 1 \mid \text{covariates}) = \Lambda(\eta_{\mathrm{H3},ict}) \ (\text{logit}) \end{aligned} \quad (3)$$

$$\begin{aligned} \eta_{\mathrm{H5},ict} &= \alpha + \beta_1 MM_{ct} + \beta_2 NDR_{ct} + \beta_3 (MM_{ct} \times NDR_{ct}) \\ &\quad + \gamma' X_{ict} + \delta_s + \tau_t \\ WC_{ict} &= \eta_{\mathrm{H5},ict} + \varepsilon_{ict} \ (\mathrm{OLS}); \ \mathrm{E}(Share_{ict} \mid \text{covariates}) = \Lambda(\eta_{\mathrm{H5},ict}) \ (\text{fractional logit}) \\ \Pr(Use_{ict} &= 1 \mid \text{covariates}) = \Lambda(\eta_{\mathrm{H5},ict}) \ (\text{logit}) \end{aligned} \quad (4)$$

In Equations (1)–(4), i indexes firms, c is economies, t is survey years, and s is industries. WC is the percentage of working capital financed through supplier credit/customer advances; $share = WC/100$; and use equals one when $WC > 0$. CDF denotes conventional digital finance, MM us mobile money, IC is insurance capacity, DI is digital infrastructure, NDR is nonlife digital readiness, and X is the locked vector of firm-level and macroeconomic controls. α is the intercept; β parameters are focal coefficients; γ is the control coefficient vector; δ_s and τ_t are industry and survey year effects; ε_{ict} is the OLS disturbance; $\eta_{\mathrm{H3},ict}$ and $\eta_{\mathrm{H5},ict}$ denote the linear predictors defined explicitly in Equations (3) and (4), respectively; and $\Lambda(\cdot)$ is the logistic function. Equation (4) preserves the executed H5 specification and, therefore, excludes CDF and IC.

4.6. Inference and Decision Rules

Standard errors are clustered by economy because the main explanatory variables vary at the country level and are repeated across firms. Cluster-robust inference is used because residuals may be correlated within economies, although its reliability depends on the number and configuration of clusters (Cameron & Miller, 2015). With 39 country clusters, the analysis reports p-values at the displayed precision and distinguishes the 1%, 5%, and 10% thresholds. The final specification does not use country fixed effects, a wild cluster bootstrap, or survey weights.

All hypothesis tests are two-sided. The results with $p < 0.10$ but $p \geq 0.05$ are treated as marginal support at the 10% level and are not described as significant at 5%. H3 requires a negative interaction at the stated threshold. H4 is judged from the pattern across the adoption and users-only intensity models, while recognizing that no formal cross-model coefficient difference test was conducted. Given the observational design, all findings are interpreted as associations rather than causal effects.

4.7. Institutional Control Sensitivity Analysis

To address the concern about observed country-level institutional conditions, we conducted a pre-specified sensitivity analysis using the World Bank Worldwide Governance Indicators (WGIs) 2026 update (World Bank, 2026; Romano et al., 2026). Regulatory Quality

(RQ) captures perceptions of the government's ability to design and implement policies and regulations that promote private sector development, whereas Rule of Law (RL) captures perceptions of adherence to societal rules, including contract enforcement, property rights, police, courts, crime, and violence. Each indicator was matched to the firm data by economy and the exact survey year, preserving all 32,049 firms and 39 economy–survey-year cells. Before estimating any outcome model, RQ and RL were screened on the 39 unique economy-year cells. Both passed the locked standalone VIF < 10 criterion, but their correlation was 0.8041, and the maximum joint institutional VIF was 5.9650; under the pre-locked rule, this triggered separate RQ-only and RL-only specifications rather than a joint specification. The full H1–H5 model families were then rerun without changing the baseline controls, industry and survey year effects, country-clustered inference, estimator, or sample restrictions. This exercise is a robustness check for sensitivity to observed institutional quality, not an identification strategy for eliminating country-level confounding.

5. Results

5.1. Descriptive Statistics

In the final sample (Table 3), firms finance an average of 10.081% of working capital through supplier credit/customer advances, whereas the median is zero. Only 28.3% of firms use the channel, confirming the empirical relevance of separating adoption from conditional intensity. The country-level standardized indices do not have firm-weighted means of zero in the final sample because country values are repeated for unequal numbers of firms and the complete-case restriction changes the represented country mix.

Table 3. Descriptive statistics for the final analytical sample.

Variable	*N*	Mean	SD	Min	Max
Working capital finance (%)	32,049	10.081	20.468	0.000	100.000
Working capital share	32,049	0.101	0.205	0.000	1.000
Adoption	32,049	0.283	0.451	0.000	1.000
Conventional digital finance	32,049	−0.087	0.717	−1.317	2.359
Mobile money	32,049	−0.637	0.662	−0.974	2.586
Insurance capacity	32,049	−0.398	0.472	−1.240	1.085
Digital infrastructure	32,049	−0.888	0.676	−1.989	0.623
Nonlife digital readiness	32,049	−0.515	0.573	−1.539	0.901
ln(permanent employees)	32,049	3.376	1.386	0.000	9.903
ln(1 + firm age)	32,049	2.823	0.683	0.000	5.357
Exporter	32,049	0.227	0.419	0.000	1.000
Foreign ownership (%)	32,049	6.470	22.425	0.000	100.000
External audit	32,049	0.582	0.493	0.000	1.000
ln(real GDP per capita)	32,049	7.897	0.748	6.209	9.412
GDP growth (%)	32,049	5.050	2.564	−7.200	9.286
Inflation (%)	32,049	5.470	4.478	−1.800	23.792
Private credit/GDP (%)	32,049	47.753	27.243	7.836	146.224

Notes: The 25th, median, and 75th percentiles are omitted from the displayed table for space; the outcome median is zero, and the 75th percentile of the percentage outcome is 10.000. Full descriptive output is included in the replication tables.

5.2. Direct Associations: H1 and H2

Table 4 reports on the direct-effect models. Conventional digital finance is positively associated with the percentage outcome ($b = 3.552$, SE = 1.340, $p = 0.0117$), the fractional share ($b = 0.392$, SE = 0.120, $p = 0.0011$), and adoption ($b = 0.497$, SE = 0.136, $p = 0.0003$). H1 is, therefore, supported across all three estimators. The coefficients are on different scales: the OLS estimate is in percentage points, whereas the fractional logit and logit coefficients are log-odds index parameters.

Table 4. Direct associations of conventional digital finance and insurance capacity with trade-related working capital finance.

Variable	OLS Percentage	Fractional Logit	Adoption Logit
Conventional digital finance	3.552 ** (1.340)	0.392 *** (0.120)	0.497 *** (0.136)
Mobile money	−2.673 * (1.541)	−0.205 (0.130)	−0.195 (0.141)
Insurance capacity	7.618 *** (1.616)	0.768 *** (0.124)	1.001 *** (0.136)
Firm controls	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes
Industry/year effects	Yes/Yes	Yes/Yes	Yes/Yes
Observations	32,049	32,049	32,048
Adjusted R^2/log likelihood	0.109	−9756.166	−17,495.511

Notes: Coefficients with country-clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-sided). OLS coefficients are percentage point effects. Fractional logit and binary logit coefficients are coefficients on the logit link index and should not be interpreted as percentage point marginal effects. Marginal effects are reported separately where calculated.

Insurance capacity is also positive in all models: $b = 7.618$ (SE = 1.616, $p < 0.001$) in OLS, $b = 0.768$ (SE = 0.124, $p < 0.001$) in fractional logit, and $b = 1.001$ (SE = 0.136, $p < 0.001$) in adoption logit. H2 is supported at the 1% level across outcomes. By contrast, the mobile money main coefficient is negative and marginal in OLS ($b = -2.673$, SE = 1.541, $p < 0.10$) but nonsignificant in the fractional and adoption models. The direct mobile coefficient is not a separate hypothesis and should not be interpreted outside the later interaction models.

5.3. Digital Infrastructure Moderation: H3

Table 5 reports the separate H3 specifications with digital infrastructure and its interaction with mobile money. The interaction is negative in OLS ($b = -4.222$, SE = 3.760, $p = 0.2685$), fractional logit ($b = -0.485$, SE = 0.313, $p = 0.1212$), and adoption logit ($b = -0.765$, SE = 0.396, $p = 0.0532$). Only the adoption estimate crosses the pre-specified 10% threshold. H3, therefore, receives marginal support at the 10% level for adoption, but it is not supported for the percentage or fractional share outcomes at conventional thresholds.

Average marginal effects clarify the nonlinear adoption result (Table 6). At the 10th and 25th infrastructure percentiles, a one standard deviation increase in mobile money is associated with adoption probability changes of 0.1087 ($p = 0.0274$) and 0.1074 ($p = 0.0275$). The effect falls to 0.0329 at the median ($p = 0.0780$), becomes −0.0528 at the 75th percentile ($p = 0.1592$), and is −0.1222 at the 90th percentile ($p = 0.0871$). Thus, the pattern moves from positive in low-infrastructure settings to negative in high-infrastructure settings, but the middle and upper-tail estimates are individually imprecise. The calculated interaction turning point in the logit index is −0.7403; the OLS and fractional logit turning points are −0.9145 and −0.8569, respectively.

Table 5. Moderating role of digital infrastructure (H3).

Variable	OLS Percentage	Fractional Logit	Adoption Logit
Mobile money	−3.861 (3.332)	−0.416 (0.268)	−0.567 * (0.344)
Digital infrastructure	5.109 (3.687)	0.249 (0.340)	−0.457 (0.391)
Mobile money × infrastructure	−4.222 (3.760)	−0.485 (0.313)	−0.765 * (0.396)
Insurance capacity	6.023 *** (1.410)	0.572 *** (0.111)	0.770 *** (0.135)
Controls and industry/year effects	Yes	Yes	Yes
Observations	32,049	32,049	32,048
Adjusted R^2/log likelihood	0.111	−9754.304	−17,532.198

Notes: Coefficients with country-clustered standard errors in parentheses. * $p < 0.10$, *** $p < 0.01$ (two-sided). OLS coefficients are percentage point effects. Fractional logit and binary logit coefficients are coefficients on the logit link index and should not be interpreted as percentage point marginal effects. Marginal effects are reported separately where calculated.

Table 6. Average marginal effect of mobile money on adoption at infrastructure percentiles.

Infrastructure Percentile	Index Value	AME	SE	*p*-Value	95% CI
10th	−1.5299	0.1087	0.0493	0.0274	[0.0121, 0.2054]
25th	−1.5200	0.1074	0.0487	0.0275	[0.0119, 0.2030]
50th	−0.9735	0.0329	0.0187	0.0780	[−0.0037, 0.0694]
75th	−0.3672	−0.0528	0.0375	0.1592	[−0.1262, 0.0207]
90th	0.1179	−0.1222	0.0714	0.0871	[−0.2623, 0.0178]

Notes: Average marginal effects are calculated from the H3 adoption logit using the saved margins dataset. CI = confidence interval.

Figure 1 displays the marginal-effect estimates and 95% confidence intervals. Figure 2 displays predicted adoption probabilities for mobile money index values of −1, 0, and 1 across the same infrastructure percentiles. The figures visualize model predictions rather than causal treatment effects.

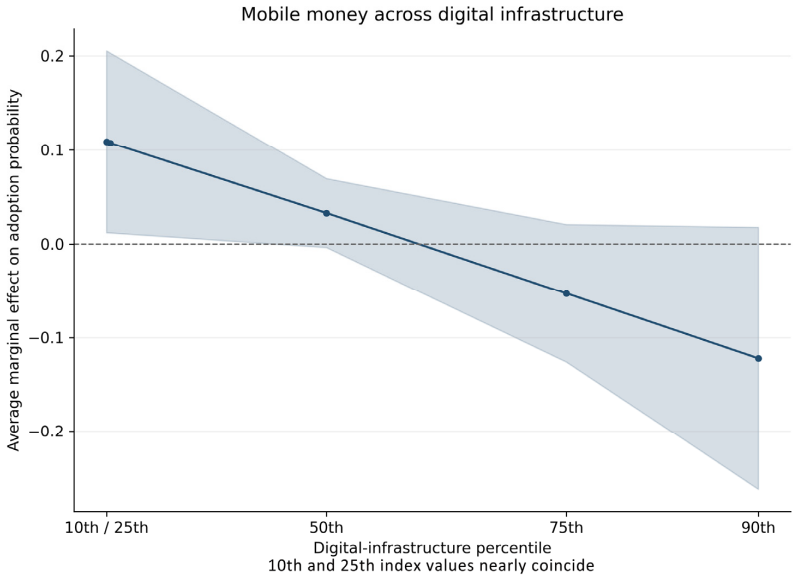


Figure 1. Average marginal effect of mobile money on adoption across digital infrastructure percentiles. The x-axis retains index spacing and labels infrastructure percentiles; corresponding index values are in Table 6.

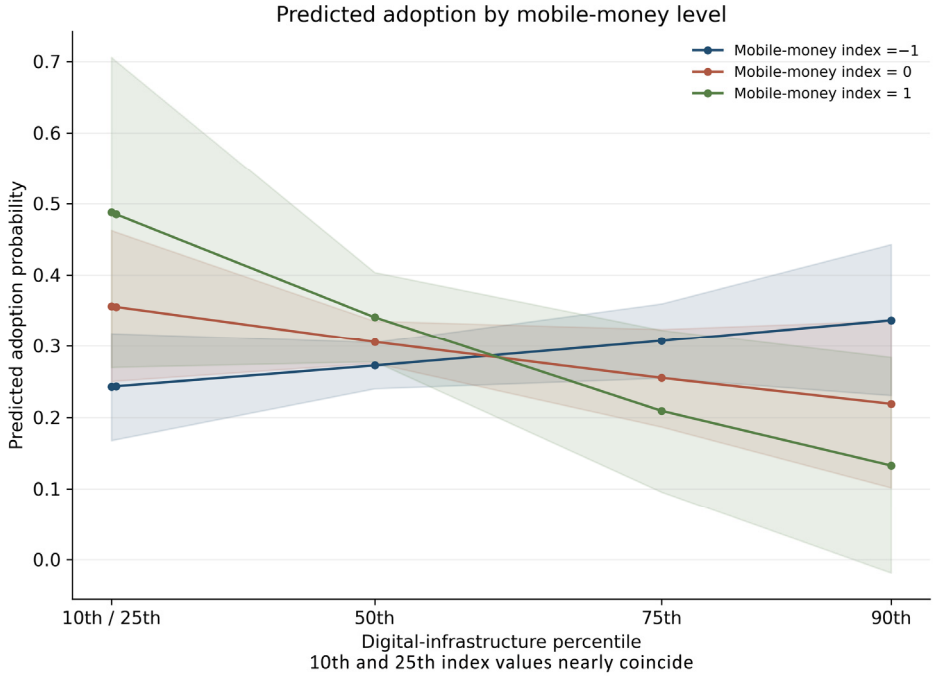


Figure 2. Predicted adoption probabilities by mobile money level and digital infrastructure. The x-axis retains index spacing and labels infrastructure percentiles; corresponding index values are in Table 6.

5.4. Adoption Versus Intensity: H4

Table 7 compares the H3 interaction across the two parts. In the adoption logit, $MM \times DI$ is −0.7653 (SE = 0.3959, $p = 0.0532$; $N = 32{,}048$). Among the 9078 users, the conditional-intensity interaction is 0.0054 (SE = 0.2129, $p = 0.9798$). The negative moderation is, therefore, present only at the adoption margin and is absent in the users-only intensity model. Under the stated decision rule, this pattern provides qualified support for H4 at the 10% level. The conclusion remains qualified because the estimators use different samples and scales and no formal cross-model difference test was performed.

Table 7. Two-part comparison of adoption and conditional intensity (H4).

Variable	Adoption Logit	Users-Only Fractional Logit
Mobile money	−0.567 * (0.344)	−0.068 (0.156)
Digital infrastructure	−0.457 (0.391)	0.808 *** (0.250)
Mobile money × infrastructure	−0.765 * (0.396)	0.005 (0.213)
Insurance capacity	0.770 *** (0.135)	−0.026 (0.096)
Controls and industry/year effects	Yes	Yes
Observations	32,048	9078
Log likelihood	−17,532.198	−5755.605

Notes: Coefficients with country-clustered standard errors in parentheses. The users-only model is restricted to trade_wc_use = 1. * $p < 0.10$, *** $p < 0.01$. Binary logit and fractional logit coefficients are coefficients on the logit link index and should not be interpreted as percentage point marginal effects. Marginal effects are reported separately where calculated.

5.5. Nonlife Digital Readiness: H5

Table 8 reports the alternative moderation models. The mobile money × nonlife digital readiness interaction is −0.9391 in the adoption logit (SE = 0.5440, $p = 0.0843$), −0.7569 in

fractional logit (SE = 0.3704, $p = 0.0410$), and −6.2441 in OLS (SE = 3.8553, $p = 0.1136$). H5 is, therefore, supported for the fractional share at the 5% level and receives marginal support for adoption at the 10% level, but it is not supported for the percentage outcome. The appropriate overall classification is partial and outcome-dependent support.

Table 8. Mobile money and nonlife digital readiness (H5).

Variable	Adoption Logit	Fractional Logit	OLS Percentage
Mobile money	−0.259 (0.164)	−0.285 ** (0.145)	−3.045 * (1.625)
Nonlife digital readiness	0.510 (0.463)	0.411 (0.274)	6.716 ** (3.097)
Mobile money × readiness	−0.939 * (0.544)	−0.757 ** (0.370)	−6.244 (3.855)
Controls and industry/year effects	Yes	Yes	Yes
Observations	32,048	32,049	32,049

Notes: Coefficients with country-clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$ (two-sided). OLS coefficients are percentage point effects. Fractional logit and binary logit coefficients are coefficients on the logit link index and should not be interpreted as percentage point marginal effects. Marginal effects are reported separately where calculated.

5.6. Robustness Check and Outcome Sensitivity

Table 9 contains two conceptually different exercises. The first two columns are outcome sensitivity analyses because they replace the main supplier credit/customer advance working capital outcome with separate trade credit-received and trade credit-granted shares. The mobile money × infrastructure interaction is positive for trade credit received ($b = 2.3713$, SE = 0.7681, $p = 0.002$; $N = 27{,}843$) and trade credit granted ($b = 2.2819$, SE = 0.8728, $p = 0.009$; $N = 28{,}002$), reversing the negative direction in the main H3 specification. These coefficients do not confirm H3 and should not be treated as robustness evidence for the same estimand: received credit places the focal firm in a buyer/borrower role, granted credit places it in a supplier/lender role, and the aggregate working capital share combines supplier credit with customer advances. Prior research shows that product characteristics, buyer market power, financing constraints, and monitoring arrangements can differ across these bilateral roles (Giannetti et al., 2011; Yang et al., 2021). Such mechanisms are plausible interpretations of the sign reversal, not mechanisms identified by the present design.

Table 9. Robustness analyses and outcome sensitivity.

Variable	Trade Credit Received	Trade Credit Granted	Alternative InsurTech OLS
Mobile money	1.224 ** (0.616)	1.127 * (0.583)	−3.799 ** (1.431)
Digital infrastructure	3.055 *** (0.985)	3.093 *** (1.031)	—
Mobile money × infrastructure	2.371 *** (0.768)	2.282 *** (0.873)	—
Insurance capacity	0.759 ** (0.313)	0.738 ** (0.288)	—
Conventional digital finance	—	—	4.640 *** (1.254)
InsurTech readiness	—	—	12.664 *** (2.147)
Controls and industry/year effects	Yes	Yes	Yes
Observations	27,843	28,002	32,049

Notes: The first two columns are fractional logit outcome sensitivity models; the third is an OLS robustness/alternative construct model for trade_wc_pct using the broader InsurTech readiness index. Coefficients use country-clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fractional logit coefficients are coefficients on the logit link index and should not be interpreted as percentage point marginal effects.

The third column is a robustness/alternative construct check because it retains the main trade-related working capital outcome while replacing insurance capacity with the broader InsurTech readiness composite. Its coefficient is positive and significant ($b = 12.664$, SE = 2.147, $p < 0.001$), while conventional digital finance remains positive ($b = 4.640$, SE = 1.254, $p < 0.001$) and mobile money is negative ($b = -3.799$, SE = 1.431, $p < 0.05$). This result indicates that the positive institutional association is not unique to the two-component insurance capacity PCA, but it does not redefine H2 or establish a specific InsurTech mechanism.

5.7. Institutional Control Robustness

Table 10 reports the institutional control sensitivity analysis. Conventional digital finance (H1) and insurance capacity (H2) remain positive and statistically supported across OLS, fractional logit, and adoption logit models under both RQ and RL controls. For H3, the *MM* × *DI* interaction remains negative in all estimators: it is nonsignificant in OLS and fractional logit, marginal at 10% in the RQ adoption model ($b = -0.794$, SE = 0.420, $p = 0.0587$), and significant at 5% in the RL adoption model ($b = -0.834$, SE = 0.388, $p = 0.0314$). The H4 users-only interaction remains null under both RQ ($b = -0.013$, SE = 0.222, $p = 0.9517$) and RL ($b = 0.065$, SE = 0.214, $p = 0.7607$), preserving the concentration of the negative moderation pattern at the adoption margin rather than conditional intensity. For H5, the *MM* × *NDR* interaction remains negative and is significant at 5% in the fractional models (RQ: $b = -0.731$, SE = 0.362, $p = 0.0438$; RL: $b = -0.702$, SE = 0.337, $p = 0.0371$), marginal at 10% in the adoption models, and nonsignificant in OLS. Thus, the main empirical pattern is broadly stable when observed Regulatory Quality and Rule of Law are controlled separately; these measured controls do not eliminate all unobserved country heterogeneity or establish causal identification.

Table 10. The institutional control robustness.

Hypothesis/Focal Term	Estimator	Submitted Baseline	+Regulatory Quality	+Rule of Law	*N*
H1: Conventional digital finance	OLS	3.552 ** (1.340) $p = 0.0117$	3.415 ** (1.308) $p = 0.0128$	3.886 *** (1.248) $p = 0.0035$	32,049
H1: Conventional digital finance	Fractional logit	0.392 *** (0.120) $p = 0.0011$	0.396 *** (0.118) $p < 0.001$	0.440 *** (0.118) $p < 0.001$	32,049
H1: Conventional digital finance	Adoption logit	0.497 *** (0.136) $p < 0.001$	0.497 *** (0.138) $p < 0.001$	0.503 *** (0.141) $p < 0.001$	32,048
H2: Insurance capacity	OLS	7.618 *** (1.616) $p < 0.001$	7.132 *** (1.480) $p < 0.001$	6.767 *** (1.477) $p < 0.001$	32,049
H2: Insurance capacity	Fractional logit	0.768 *** (0.124) $p < 0.001$	0.738 *** (0.108) $p < 0.001$	0.696 *** (0.107) $p < 0.001$	32,049
H2: Insurance capacity	Adoption logit	1.001 *** (0.136) $p < 0.001$	1.003 *** (0.140) $p < 0.001$	0.988 *** (0.135) $p < 0.001$	32,048
H3: *MM* × digital infrastructure	OLS	−4.222 (3.760) $p = 0.2685$	−4.388 (3.911) $p = 0.2689$	−4.077 (3.673) $p = 0.2739$	32,049
H3: *MM* × digital infrastructure	Fractional logit	−0.485 (0.313) $p = 0.1212$	−0.515 (0.331) $p = 0.1194$	−0.497 (0.306) $p = 0.1044$	32,049
H3: *MM* × digital infrastructure	Adoption logit	−0.765 * (0.396) $p = 0.0532$	−0.794 * (0.420) $p = 0.0587$	−0.834 ** (0.388) $p = 0.0314$	32,048

Table 10. *Cont.*

Hypothesis/Focal Term	Estimator	Submitted Baseline	+Regulatory Quality	+Rule of Law	*N*
H4: *MM* × digital infrastructure	Users-only fractional logit	0.005 (0.213) $p = 0.9798$	−0.013 (0.222) $p = 0.9517$	0.065 (0.214) $p = 0.7607$	9078
H5: *MM* × nonlife digital readiness	Adoption logit	−0.939 * (0.544) $p = 0.0843$	−0.940 * (0.544) $p = 0.0840$	−0.976 * (0.535) $p = 0.0683$	32,048
H5: *MM* × nonlife digital readiness	Fractional logit	−0.757 ** (0.370) $p = 0.0410$	−0.731 ** (0.362) $p = 0.0438$	−0.702 ** (0.337) $p = 0.0371$	32,049
H5: *MM* × nonlife digital readiness	OLS	−6.244 (3.855) $p = 0.1136$	−6.133 (3.872) $p = 0.1215$	−5.497 (3.659) $p = 0.1413$	32,049

Notes: Each cell reports the coefficient, country-clustered standard error in parentheses, and Stata *p*-value below the estimate (values below 0.001 are reported as $p < 0.001$). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-sided). RQ = Regulatory Quality; RL = Rule of Law; *MM* = mobile money; *DI* = digital infrastructure; *NDR* = nonlife digital readiness. RQ and RL are added separately under the pre-result collinearity rule. Baseline estimators, controls, industry effects, survey year effects, clustering, and sample restrictions are unchanged. H4 adoption is represented by the H3 adoption row because the executed H4 adoption specification is identical to H3 adoption.

Table 11 summarizes the hypothesis decisions without suppressing null or sign-reversing evidence.

Table 11. Hypothesis decisions under the pre-specified two-sided thresholds.

Hypothesis	Prediction	Decision	Evidence Boundary
H1	Conventional digital finance: positive direct association	Supported	Positive at 5% or better in OLS, fractional logit, and adoption logit
H2	Insurance capacity: positive direct association	Supported	Positive at 1% in all three models
H3	Infrastructure negatively moderates mobile money	Marginal support at 10%	Adoption interaction $p = 0.0532$; OLS and fractional interactions nonsignificant
H4	Moderation concentrated in adoption rather than intensity	Qualified support at 10%	Adoption $p = 0.0532$; users-only intensity $p = 0.9798$; no formal cross-model test
H5	Nonlife digital readiness negatively moderates mobile money	Partial support	Fractional $p = 0.0410$; adoption $p = 0.0843$; OLS $p = 0.1136$

Notes: "Marginal support" always means $p < 0.10$ but $p \geq 0.05$. Null and sign-reversing robustness evidence is retained rather than reclassified.

6. Discussion

6.1. Interpretation of the Direct Associations

The consistent H1 result suggests that conventional digital finance depth and trade-related working capital finance coexist as complementary capabilities in the represented firm environments. This pattern is consistent with evidence from Ghana that digital payment adoption is associated with both the demand for and supply of trade credit among informal firms (Abdulai et al., 2024) and with a Chinese-listed firm study associating city-level digital finance with longer receivable, payable, and net recovery periods (Xu et al., 2025). At the same time, the literature does not imply that digitalization uniformly expands trade credit: Zhang et al. (2025) find lower reliance on supplier financing alongside greater credit provi-

sion to downstream customers after customer digitalization in a different listed firm setting. The difference is substantively informative rather than a contradiction manufactured from unlike designs: the present measure is a national conventional digital finance environment, whereas corporate digital transformation studies measure firm-level technology strategy and often isolate one side of the buyer–supplier relationship. The present association should, therefore, not be read as evidence that digital finance causes firms to take more credit or that a larger working capital share is necessarily welfare-improving.

H2 is statistically stronger, but the construct still requires a cautious interpretation. The headline index captures the national insurance capacity by nonlife insurance premiums and insurance assets; it does not measure the use of insurance technologies at the company level. The positive association is in line with a more risk-sharing, monitoring, and financial contracting environment (Yang et al., 2021). The wider literature on finance also shows that institutional and macroeconomic conditions can interact with company characteristics to shape financial adjustment (Botta & Colombo, 2022), which supports the treatment of the capacity of the national financial system as a conditional environment rather than as a separate behavior of firms. The alternative construct of InsurTech readiness shows that the positive association is not unique to the two-tier insurance PCA but that the available data do not distinguish whether it is due to trade credit insurance, data sharing, supplier confidence, or other institutional channels.

6.2. Moderation, Leapfrogging, and the Adoption Margin

The H3 estimate is consistent with the fact that mobile money is becoming less distinct as wider infrastructure is improved. At the lower infrastructure percentiles, its marginal relationship to adoption is positive and significant before then decreasing and crossing zero as the index of infrastructure grows. The transfer cost discussion in Aron (2018) motivates the potential importance of mobile money under inadequate transport infrastructure, and more recent evidence shows that network coverage is positively associated with uptake and that the technology is different between mobile and bank-based financial systems (Mothobi & Kebotsamang, 2024). This result, therefore, refines rather than overturns the literature on infrastructure: it can facilitate digital finance in general, but at the same time reduce the relative distinctiveness of a single mobile money channel. The evidence is mixed as the interaction on adoption does not reach 5 percent, and neither of the continuous outcome models shows a significant interaction.

H4 places this pattern at the adoption margin. The interaction is only marginally significant at 10 percent in the adoption model but is virtually non-existent in companies that are already using the channel. This distinction is consistent with the idea that mobile transaction capacity may be important for entering into a credit relationship, while the intensity of financing after entry may be more dependent on the terms of trade, product characteristics, bargaining power, production requirements, and counterparty risk (Giannetti et al., 2011; Yang et al., 2021). The comparison also adds evidence from the case of mobile money and trade credit in one country, showing that mobile money can be associated with both the acquisition and the offer of trade credit, and that the relevant range can vary depending on the ecosystem (Tetteh et al., 2025). Since the two estimators use different samples and scales and no formal test for the difference in coefficients between models has been carried out, the evidence is qualified as evidence rather than evidence that the coefficients are different.

H5 extends this argument to a narrower measure of nonlife and digital preparedness. The fractional share model shows a negative interaction at the 5 percent level, and the adoption variable shows a negative interaction at the 10 percent level, while OLS interaction is not significant. The resulting support is, therefore, partial and outcome-contingent.

Ecosystem theory provides a vocabulary for interdependence and complementarity (Adner, 2017; Jacobides et al., 2018). Distinguishing adoption, conditional allocation, and bilateral credit flows is this study's application of that framework, rather than a financing margin prediction tested in those sources. The results limit the theoretical claim: joint institutional and digital readiness may condition the relative role of mobile money, but the direction is not uniform across different operationalizations of trade-related finance.

6.3. Theoretical Contributions

This theoretical contribution is a boundary condition refinement of the ecosystem view, not a claim that ecosystem theory predicts trade credit directly. Instead, Adner (2017) and Jacobides et al. (2018) focus on interdependence, alignment, modularity, and complementarity among the various activities and actors. In this context, the results reveal why conventional digital finance, mobile money, insurance capacity, and digital infrastructure should not be lumped into a single digitalization variable: the association between conventional digital finance is always positive, whereas the association between mobile money is contingent on surrounding capabilities and on whether the outcome measures entry or intensity. This adds to recent firm-level evidence on mobile money and trade credit by placing that relationship within a broader national capability structure rather than treating the technology in isolation (Tetteh et al., 2025).

The sensitivity of the results increases this contribution. Positive mobility money × infrastructure coefficients for trade credits received and granted differ from the negative interaction in the main mix of finance for working capital. As the receiving loan places the focal enterprise on the buyer side and the granting loan places the supplier on the supplier side, the three outcomes reflect different funding roles, bargaining positions, and exposure to risk. Giannetti et al. (2011) show that product characteristics and buyer market power are linked to the terms of trade credit, while Yang et al. (2021) show that the monitoring and smoothing functions depend on the structure of the trade credit insurance. These studies do not directly explain the current sign reversal; they show why different ranges may plausibly be generated by bilateral roles. The reversal is, therefore, considered to be a sensitivity to outcome and a theoretical limit, rather than confirmation of the main hypothesis of moderation.

6.4. Practical and Policy Implications

This has the practical consequence of avoiding treating national digital finance indicators as interchangeable policy objectives. The wider use of accounts, digital payments, and cards can coexist with business-to-business financial relations, while the relative role of mobile money depends on the underlying financial infrastructure and architecture. Evidence that network coverage affects the uptake of digital finance in different ways in mobile and bank-led systems reinforces the need for a sequencing that is consistent with the prevailing delivery model (Mothobi & Kebotsamang, 2024). Similarly, regulation and ecosystem organization are important for the expansion of digital credit and mobile money (Le et al., 2023; Lashitew et al., 2019). Because the design is observational, these results support differentiated diagnostic attention rather than a causal link for the spread of one technology to the detriment of another.

For firms, suppliers, insurers, and lenders, the findings emphasize that settlement reliability, transaction records, risk-bearing capacity, and counterparty position are linked but not equivalent. A higher share of supplier credit or customer advances should not automatically be interpreted as beneficial: reverse-factoring outcomes vary with financial conditions, and trade credit financing has been associated with lower performance in some settings (Beyer & Herzog, 2021; Mahmud et al., 2022). Managers should, therefore, evaluate

the price and timing of operating finance, bargaining position, default exposure, supply chain continuity, and available settlement channels together. The sign reversals for received and granted credit further imply that a policy or managerial interpretation that is valid for buyers need not transfer mechanically to suppliers.

6.5. Limitations and Future Research

Several limitations qualify the findings. First, the firm-level design is observational and repeated cross-sectional, so unobserved firm or institutional characteristics may explain part of the reported associations. Second, the focal country-level constructs vary across economies, and each represented economy contributes one economy–year cell to the complete-case sample; country fixed effects would, therefore, absorb the realized cross-sectional variation that identifies these constructs. Omitting country fixed effects preserves that variation but cannot eliminate time-invariant national confounding. Unobserved dimensions such as legal and enforcement quality, Regulatory Quality, financial development, or broader business institutions could be correlated with both the country-level digital/insurance environment and firms' working capital choices (Fasano et al., 2024; Le et al., 2023; Botta & Colombo, 2022). This concern applies especially to the cross-level interaction coefficients underlying H3 and H5: the present design cannot establish that those interaction estimates are unbiased, and neither the direction nor magnitude of any resulting omitted variable bias can be identified from the available data. Third, inference relies on 39 country clusters, so precision remains sensitive to the number and configuration of clusters (Cameron & Miller, 2015). Future research using repeated country waves, policy changes, stronger institutional panels, or credible quasi-experimental variation could address these limitations more directly. The institutional control sensitivity analysis reduces one observable dimension of this concern by adding RQ and RL separately, but it cannot rule out residual institutional or other country-level confounding, and it does not change the associational interpretation.

7. Conclusions

Using 32,049 enterprises in 39 economies surveyed in 2014–2020, the study found that traditional digital finance and national insurance capacity are positively correlated with the use of supplier credit and customer advances by enterprises, percentages, fractions, and acceptance models. Digital infrastructure weakens the link between mobile money and adoption only at the adoption margin, where interaction is only marginally significant at 10 percent; it does not significantly weaken the percentage or fractional intensity. The adoption-versus-users comparison, therefore, supports H4 only in a qualified 10% pattern. Nonlife digital readiness produces partial support: its interaction with mobile money is negative at 5% for the fractional share and at 10% for adoption, but not significant in OLS.

The results favor disaggregated ecosystem interpretation. Conventional digital rails, mobile money, insurance capacity, and infrastructure play different roles, and their associations depend on whether the outcome captures adoption, conditional intensity, or a distinct trade credit flow. Positive interaction reversals for trade credit received and granted are material counterevidence to any universal substitution claim. The contribution is consequently not a causal ranking of technologies but a transparent map of robust, marginal, null, and outcome-sensitive associations that future panel, quasi-experimental, and transaction-level research can test more decisively.

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Appendix A. Economy Coverage

The final analytical sample includes the following 39 economies: Albania, Armenia, Benin, Bolivia, Cameroon, Chad, Colombia, Côte d'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Georgia, Guatemala, Honduras, India, Indonesia, Kenya, the Kyrgyz Republic, Malawi, Malaysia, Mali, Mongolia, Morocco, Mozambique, Nicaragua, Niger, Nigeria, Paraguay, Peru, the Philippines, Romania, Rwanda, Senegal, Thailand, Togo, Türkiye, Viet Nam, and Zambia.

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