

Adoption, Not Infrastructure: FinTech Ecosystems and Formal Entrepreneurial Entry in Sub-Saharan Africa

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Abstract

We show that FinTech ecosystem development is positively associated with formal entrepreneurial entry across Sub-Saharan Africa. Using a panel of 46 economies from 2014 to 2022, we construct a composite FinTech ecosystem index through a two-stage principal component analysis that separates demand-side adoption from supply-side infrastructure. A one-standard-deviation increase in the composite index is associated with a 0.182 increase in the log of one plus new business density. Channel decomposition reveals that this association is driven by demand-side adoption: supply-side infrastructure is negatively associated with formal entry once adoption is held constant, consistent with incumbent capture of digital channels in contexts where behavioural adoption has not kept pace with infrastructure provision. Private credit depth does not moderate the relationship, consistent with segmented credit markets in Sub-Saharan Africa. Broad monetary depth weakens the association, suggesting partial substitution between digital financial services and conventional monetary intermediation. Identification diagnostics support a directional interpretation while acknowledging the limits of observational panel evidence. The results indicate that FinTech policies aimed at stimulating formal entrepreneurship should prioritise adoption capabilities and effective use over infrastructure expansion alone.

JEL Classification: G21; L26; O16; O33; O55

Keywords: FinTech ecosystem; formal entrepreneurial entry; Sub-Saharan Africa; channel decomposition; monetary substitution

1. Introduction

Sub-Saharan Africa has become the global centre of mobile money diffusion, yet this transformation has not produced comparable progress in formal business formation. By 2024, mobile money account ownership in the region had reached 40 per cent of adults, approximately 290 million accounts and almost three times the 2014 level, and 58 per cent of adults held either a mobile money or a financial institution account (Klapper et al., 2025). Over the same period, formal entrepreneurial entry remained persistently low. Average new business density was 1.4 newly registered firms per 1,000 working-age adults in 2014 and reached only 1.8 in 2020, below the world average of 3.4 and below corresponding rates in East Asia and the Pacific, Europe and Central Asia, and Latin America and the Caribbean (World Bank, 2024). This divergence raises a direct empirical question: does the expansion of digital financial ecosystems translate into formal entrepreneurial entry, and, if so, through which channels and under what macro-financial conditions?

Existing evidence suggests that digital finance can relax constraints relevant to entrepreneurial activity. At the micro level, mobile money and related digital financial services are associated with expanded access to finance, trade credit, transactional efficiency, self-employment, and firm productivity across several Sub-Saharan African economies (Dalton et al., 2023; Gosavi, 2018; Kedir & Kouame, 2022; Konte & Tetteh, 2023; Tetteh et al., 2025). At the macro level, cross-country studies document that digital technologies improve financial inclusion in Sub-Saharan Africa, that digital financial inclusion supports GDP per capita growth conditional on institutional quality, and that FinTech development expands digital finance availability for SMEs and entrepreneurship across African economies (Chinoda & Kapingura, 2023; Kouladoun et al., 2022; Sanga & Aziakpono, 2024; Voptia & Stukalina, 2025). Notwithstanding these contributions, the literature has paid comparatively little attention to whether FinTech ecosystem development translates into formal entrepreneurial entry, a distinct outcome linked to business demography, registration, and market formalisation.

Three gaps motivate this study. First, much of the cross-country evidence focuses on financial inclusion, the availability of SME finance, or aggregate growth rather than on formal business entry (Chinoda & Kapingura, 2023; Sanga & Aziakpono, 2024). Second, existing FinTech measures treat the phenomenon as a single aggregate, thereby obscuring the distinction between behavioural adoption and infrastructure provision, a

distinction that is theoretically important because entrepreneurial effects may arise not only from infrastructure availability but also from the active use of digital financial services for payments, savings, borrowing, and transaction record-keeping (Aron, 2018; Dalton et al., 2023). Third, relatively little is known about how broader financial conditions shape the FinTech–entry relationship, even though financial depth and macro-financial structure are known to condition entrepreneurial dynamics (Chinoda & Kapingura, 2023; Munemo, 2018; Noah & Olalekan, 2025).

To address these gaps, we examine the relationship between FinTech ecosystem development and formal entrepreneurial entry across 46 Sub-Saharan African economies from 2014 to 2022. We conceptualise the FinTech ecosystem as a two-dimensional construct comprising demand-side adoption capabilities and supply-side infrastructure enablers, consistent with ecosystem perspectives that emphasise the interaction of actors, infrastructures, institutions, and user capabilities in shaping entrepreneurial and digital-finance outcomes (Molla & Biru, 2023; Senyo et al., 2021; Spigel, 2022; Spigel & Harrison, 2018; Wurth et al., 2023). Empirically, we construct a composite FinTech ecosystem index through a two-stage principal component analysis that derives separate demand and supply sub-indices from Global Findex behavioural indicators and World Development Indicators infrastructure variables, then combines them into a composite measure. We then estimate two-way fixed-effects models of new business density, decompose the composite index into its demand and supply components, and examine whether private credit depth and broad monetary depth moderate the FinTech–entry relationship.

The analysis produces three substantive findings. A one-standard-deviation increase in the composite ecosystem index is associated with a 0.182 increase in the log of one plus new business density. Channel decomposition reveals that this relationship is driven primarily by demand-side adoption. In contrast, supply-side infrastructure is negatively associated with formal entry once adoption is held constant, a finding consistent with incumbent capture of digital channels in contexts where population-level behavioural adoption has not kept pace with infrastructure provision. Moderation analysis further shows that the positive FinTech–entry association declines as broad monetary depth rises and becomes statistically weak in the upper tail of the broad-money distribution, consistent with partial substitution between FinTech-enabled services and conventional monetary

intermediation; private credit depth, by contrast, does not significantly moderate the relationship, consistent with the structural segmentation of formal credit markets in Sub-Saharan Africa (Beck et al., 2019). Identification diagnostics, including Hausman–Wu tests, control-function diagnostics, lead–lag specifications, reverse-prediction checks, and system GMM estimates, are consistent with a directional interpretation from FinTech ecosystem development to formal entrepreneurial entry, while recognising the limits of observational panel evidence (Arellano & Bover, 1995; Blundell & Bond, 1998; Hausman, 1978; Wu, 1973).

These findings contribute to the literature in three respects. First, decomposing the FinTech ecosystem into adoption and infrastructure components reveals an asymmetry: positive demand-side and negative supply-side effects that aggregate measures would conceal; this improves on approaches that rely on FinTech firm intensity or composite digital finance proxies (Chinoda & Kapingura, 2023; Sanga & Aziakpono, 2024). Second, linking FinTech ecosystem development directly to formal entrepreneurial entry, rather than to financial inclusion, SME finance availability, or aggregate growth (Kouladoun et al., 2022; Chinoda & Kapingura, 2023; Sanga & Aziakpono, 2024), connects the digital finance literature to the business demography literature in a way that prior cross-country work has not. Third, introducing a zero-crossing diagnostic that distinguishes attenuation from localised reversal in interaction-effect specifications addresses an interpretive gap in applied panel moderation analysis (Assaf et al., 2020; Baranger et al., 2023; Becker et al., 2018).

The findings have direct implications for digital entrepreneurship policy in Sub-Saharan Africa. Infrastructure expansion alone is unlikely to generate broad-based formal entry unless accompanied by behavioural adoption, merchant usability, consumer trust, interoperability, and digital financial capability. This implication is consistent with evidence that digital financial services become economically consequential when they reduce transaction frictions, generate usable financial records, and complement existing financial relationships (Aron, 2018; Konte & Tetteh, 2023; Dalton et al., 2023). Policies aimed at stimulating formal entrepreneurship through FinTech should therefore prioritise effective use over infrastructure provision in isolation.

The remainder of the paper is organised as follows. Section 2 develops the theoretical and conceptual framework, reviews the literature on FinTech and entrepreneurship in Sub-Saharan Africa, and derives the hypotheses. Section 3 describes the data, the construction and validation of the FinTech ecosystem index, the econometric

specifications, and the identification strategy. Section 4 presents the empirical results, including the baseline estimates, channel decomposition, moderation analysis, marginal-effect diagnostics, endogeneity checks, and robustness tests. Section 5 discusses the theoretical, methodological, and policy implications, outlines the limitations, and concludes.

2. Theory, Literature, and Conceptual Framework

2.1 The Ecosystem Perspective

Entrepreneurial ecosystems are integrated configurations of actors, institutions, infrastructure, resources, capabilities, and networks that jointly produce new venture formation within a defined territorial context (Spigel & Harrison, 2018). Rather than treating new venture creation as an isolated individual act, this perspective emphasises the interdependence between entrepreneurs and the wider institutional, financial, technological, and social conditions that enable or constrain entry. Consistent with this interdependence, process-oriented accounts show that entrepreneurial activity feeds back into the ecosystem by generating capital, skills, knowledge, and network ties that shape subsequent rounds of entry (Frimanslund, 2022; Shi & Shi, 2021; Wurth et al., 2023).

Applied to FinTech, the ecosystem perspective shifts analytical attention from individual digital financial products to the wider configuration of services, infrastructures, institutions, intermediaries, and users that jointly determine whether digital finance can be produced, delivered, and used at scale (Alaassar et al., 2021; Koroleva, 2022; Molla & Biru, 2023). This framing is particularly relevant in Sub-Saharan Africa, where mobile money and digital finance have evolved through interactions among regulators, banks, mobile network operators, FinTech firms, agent networks, and end users. Senyo et al. (2021), for example, show that Ghana's mobile money ecosystem is shaped by innovative, collaborative, protectionist, equitable, legitimising, and sustaining practices, while Molla and Biru (2023) trace the evolution of Africa's FinTech ecosystem from mobile money to broader digital finance and innovative FinTech, emphasising the interaction between infrastructure provision and behavioural diffusion.

Building on this literature, this study defines a national FinTech ecosystem as the integrated set of demand-side adoption capabilities and supply-side infrastructure enablers that determine whether digital financial services

can be produced, delivered, and used at scale. This definition is intentionally operational: it identifies the two measurable dimensions suited to cross-country panel analysis, behavioural adoption and infrastructural provision, while remaining grounded in the ecosystem literature's emphasis on interdependence.

2.2 The FinTech–Entrepreneurship Nexus in Sub-Saharan Africa

Empirical research on FinTech and entrepreneurship in Sub-Saharan Africa has developed along two complementary strands, the first using household-, entrepreneur-, or firm-level data to examine how digital financial services affect entrepreneurial behaviour and firm outcomes, and the second using macro-level or cross-country panel data to examine relationships among digitalisation, financial inclusion, financial development, entrepreneurship, and growth.

At the micro level, evidence from Sierra Leone indicates that FinTech adoption, particularly mobile money, enhances transactional capabilities and facilitates information exchange among entrepreneurs, customers, and ecosystem actors (Arslan et al., 2021). Consistent with these findings, firm-level evidence from Eastern Sub-Saharan Africa shows that mobile-money-using firms are more likely to obtain loans or lines of credit and are more productive than non-users (Gosavi, 2018). Studies from Kenya further show that mobile money supports trade credit, external finance mobilisation, and firm productivity, especially when combined with traditional financial services (Konte & Tetteh, 2023; Tetteh et al., 2025), while related evidence from Burkina Faso and Cameroon emphasises the relevance of FinTech for women's entrepreneurship and financially constrained entrepreneurs (Kedir & Kouame, 2022).

At the macro level, a growing body of panel evidence documents that digitalisation is associated with improvements in financial inclusion and financial development across Sub-Saharan Africa. ICT penetration raises financial inclusion outcomes across 43 Sub-Saharan African countries (Kouladoun et al., 2022), digital financial inclusion supports GDP per capita growth with institutional quality strengthening the effect (Chinoda & Kapingura, 2023), and FinTech development expands digital finance availability for SMEs and entrepreneurship across African economies (Sanga & Aziakpono, 2022; Sanga & Aziakpono, 2024). Notwithstanding these contributions, three gaps remain. First, macro-level studies typically examine financial inclusion, SME finance availability, or aggregate growth rather than formal entrepreneurial entry, the movement

from latent, informal, or subsistence activity into legally registered business formation. Second, existing FinTech measures rely on firm counts, ICT indicators, or broad digital finance proxies that do not distinguish infrastructure provision from behavioural adoption. Third, relatively little is known about whether the FinTech–entry relationship depends on macro-financial structure, particularly the depth of credit markets and monetary intermediation.

The closest comparator is Sanga and Aziakpono (2024), who show that FinTech expansion is heterogeneously associated with improvements in SME-oriented digital finance and entrepreneurship, particularly where digital finance conditions and institutions are stronger. However, their FinTech measure relies on firm expansion and digital finance intensity, whereas the present study decomposes ecosystem development into demand-side adoption and supply-side infrastructure and links it directly to formal entrepreneurial entry density. Similarly, Chinoda and Kapingura (2023) use a dynamic panel framework to examine digital financial inclusion and GDP per capita growth; this study examines formal entry. The present analysis thus complements existing work by addressing all three gaps simultaneously.

2.3 Transmission Channels: Access, Transaction Costs, and Information

Three overlapping channels link FinTech ecosystem development to formal entrepreneurial entry: access, transaction costs, and information. These channels jointly motivate the indicator–mechanism mapping in Section 2.4.

Access. The access channel operates through expanding basic financial service availability. Mobile money accounts and financial institution accounts allow individuals and microenterprises to store value, receive payments, make transfers, and interact with formal financial systems. Conceptually, mobile money functions as "recorded cash" that connects previously unbanked users to savings, payments, and credit-scoring systems (Aron, 2018). Consistent with this logic, firm-level evidence shows that mobile-money-using enterprises are more likely to obtain loans or lines of credit and are more productive than non-users (Gosavi, 2018), suggesting that account ownership and active financial use indicate not merely inclusion in a narrow sense but the capacity to participate in formal market exchange.

Transaction costs. The transaction-cost channel operates by reducing the costs, risks, and inconvenience of exchange. Mobile payments can lower cash-handling costs, travel time, theft risk, payment delays, and the frictions associated with transacting across distance. Accordingly, mobile money users in Côte d'Ivoire and Tanzania are substantially more likely to sell in distant markets, consistent with mobile payments reducing market participation costs (Yao et al., 2022). General-equilibrium modelling with Kenyan enterprise data further shows that mobile money payments reduce theft risk, relax enforcement constraints on trade credit, and improve entrepreneurial performance (Beck et al., 2018), while experimental and survey evidence from Kenyan SMEs confirms that e-payment technologies achieve high take-up once transaction-cost barriers are reduced (Dalton et al., 2017, 2018).

Information. The information channel operates through the digital records generated by financial transactions. Mobile money deposits, withdrawals, transfers, and payments create transaction histories that reduce asymmetric information between entrepreneurs and financial service providers. A field experiment with Kenyan SMEs shows that encouraging e-payment adoption increased subsequent access to mobile loans, a result interpreted as arising from improved transaction records and reduced information asymmetry (Dalton et al., 2023). More broadly, mobile money transactions generate a financial history record that can support algorithmic credit scoring and risk assessment (Aron, 2018).

Although these channels are analytically distinct, they are empirically overlapping: a mobile money account simultaneously expands access, reduces transaction costs, and generates information useful for screening and monitoring. The purpose of the channel framework is therefore not to assign each indicator exclusively to a single mechanism, but to ensure that each constituent measure of the composite index is theoretically anchored rather than driven solely by data availability.

2.4 Indicator–Mechanism Mapping

Table 1 maps each constituent indicator to its principal theoretical channel. Demand-side indicators capture behavioural adoption of digital and formal financial services. Supply-side indicators capture the infrastructure required for digital financial services to operate at scale.

Table 1. Indicator–Mechanism Mapping for the Composite FinTech Ecosystem Index

Indicator	Source	Description	Principal channel(s)
Demand-side indicators			
Mobile money account ownership	Findex	% adults 15+ with a mobile money account	Access; information
Financial institution account	Findex	% adults 15+ with an FI account	Access
Made a digital payment	Findex	% adults 15+ who made a digital payment in the past year	Transaction costs
Mobile/internet bill payment	Findex	% adults 15+ who used mobile/internet to pay bills	Transaction costs
Saved using mobile money	Findex	% adults 15+ who saved via a mobile money account	Information
Borrowed using mobile money	Findex	% adults 15+ who borrowed using mobile money	Information
Supply-side indicators			
Individuals using the internet	WDI (IT.NET.USER.ZS)	% of population using the internet	Foundational infrastructure

Indicator	Source	Description	Principal channel(s)
Mobile cellular subscriptions	WDI (IT.CEL.SETS.P2)	Subscriptions per 100 inhabitants	Device infrastructure
Fixed broadband subscriptions	WDI (IT.NET.BBND.P2)	Subscriptions per 100 inhabitants	Bandwidth infrastructure
Electricity access	WDI (EG.ELC.ACCS.ZS)	% of population with access to electricity	Energy infrastructure

Note: Findex = Global Findex Database. WDI = World Development Indicators. Channels follow the conceptual structure in Section 2.3. Electricity access is included because digital financial services require reliable energy infrastructure to operate at scale, and FinTech development effects are conditional on energy availability (Etudaiye-Muhtar et al., 2023). Each indicator is anchored in at least one theoretically supported mechanism linking digital finance to formal entrepreneurial entry, addressing the recurring critique that FinTech and digital development indices rely on data availability rather than mechanism-based selection (Ha et al., 2025).

2.5 Moderation: Credit Depth and Monetary Substitution

The relationship between FinTech ecosystem development and formal entrepreneurial entry is unlikely to be invariant across macro-financial contexts. Two dimensions of the financial environment are particularly relevant: the depth of formal credit markets and the depth of monetary intermediation.

A substantial literature links financial development to entrepreneurial dynamics. Munemo (2018) shows that financial development, measured across depth, access, and efficiency, increases new business density in African economies and conditions the effect of foreign direct investment on entrepreneurship. Klapper and Love (2010) find that greater domestic credit to the private sector is associated with higher new firm registration. Klapper et al. (2014) further show that deeper financial systems condition how entrepreneurship responds to macroeconomic shocks, with new firm registration becoming more procyclical where entrepreneurs are more dependent on external finance. At the same time, the "too much finance" literature indicates that the relationship between credit depth and economic performance can become non-linear at high levels of financial development; Arcand et al. (2015) show that the marginal effect of private credit on growth can turn negative when credit-to-GDP becomes very high. These findings motivate treating private credit depth as a potential moderator of the FinTech–entrepreneurship relationship.

In Sub-Saharan Africa, however, the structure of formal credit markets complicates the expected role of private credit. African banking sectors are often relatively stable and liquid but lend comparatively little to the private sector, while firms and households remain less likely to use formal financial services than their counterparts in other developing regions (Beck & Cull, 2013; Beck et al., 2019). Rural finance studies further show that many firms and households, particularly in rural and low-income areas, rely on internal funds, microfinance, and informal arrangements rather than bank credit (De Cleene & Wood, 2004; Van Empel, 2010). Aggregate private credit depth may therefore reflect lending to firms already integrated into the formal banking system rather than marginal credit availability for prospective entrants. In such a segmented credit environment, private credit depth may condition the FinTech–entry relationship only weakly.

Broad monetary depth captures a different dimension of financial structure. Typically proxied by broad money to GDP, monetary depth reflects the development of deposit-taking, payment, savings, and liquidity-management

systems in the conventional financial sector. In economies with more developed financial systems, banks and related intermediaries already provide many services that FinTech platforms also seek to deliver, including payments, savings, and short-term liquidity support (Beck et al., 2019). Digital finance may therefore fill substantial gaps in monetarily shallow economies but substitute for existing services in monetarily deeper ones. This substitution logic is consistent with evidence that new firm creation is more closely tied to formal financial conditions where financial systems are deeper, and banking shocks transmit more strongly into entry dynamics (Klapper et al., 2014; Klapper & Love, 2010).

Methodologically, interaction effects can be difficult to interpret because a negative interaction coefficient does not, by itself, indicate whether the underlying effect attenuates or reverses sign within the support of the moderator. Prior work documents instability, sign reversal, and interpretive ambiguity in interaction models, particularly when marginal effects vary across the distribution of the moderator (Assaf et al., 2020; Baranger et al., 2023; Becker et al., 2018). To distinguish attenuation from localised reversal, we employ the zero-crossing diagnostic described in Section 3.6, which identifies the point at which the estimated marginal effect equals zero.

These arguments yield four hypotheses:

H1. FinTech ecosystem development is positively associated with formal entrepreneurial entry in Sub-Saharan African economies.

H2. Demand-side adoption is positively associated with formal entrepreneurial entry, while supply-side infrastructure has an ambiguous or potentially negative association when isolated from corresponding demand-side adoption.

H3. Private credit depth does not significantly moderate the relationship between FinTech ecosystem development and formal entrepreneurial entry.

H4. Broad monetary depth negatively moderates the relationship between FinTech ecosystem development and formal entrepreneurial entry.

2.6 Positioning

This study differs from the most directly comparable existing work in three respects. First, the measurement strategy departs from Sanga and Aziakpono (2024), the closest substantive comparator, who proxy FinTech development using FinTech firm expansion and digital finance intensity across 47 African countries. Their approach captures FinTech activity at the firm level but does not decompose the ecosystem into adoption and infrastructure dimensions, which is the basis for testing H2. The two-stage PCA used here enables a channel-level analysis that firm-count measures cannot support. Second, the dependent variable differs from Chinoda and Kapingura (2023), who apply a dynamic panel framework to digital financial inclusion and GDP per capita growth. Examining formal entrepreneurial entry density rather than aggregate growth reduces the inferential distance between FinTech ecosystem development and its entrepreneurial consequences and connects the analysis directly to the business demography literature. Third, the moderation analysis introduces a zero-crossing diagnostic that locates the threshold at which the estimated marginal effect of FinTech ecosystem development changes sign, consistent with the empirical support for the moderator. This diagnostic addresses a recurring interpretive problem in applied interaction-effect analysis, distinguishing attenuation from localised reversal, and is generalisable beyond the present application (Assaf et al., 2020; Baranger et al., 2023; Becker et al., 2018).

3.1 Sample and Data Sources

The empirical analysis uses a country–year panel of 46 Sub-Saharan African economies observed annually from 2014 to 2022, yielding 414 country–year observations. The starting year is determined by Global Findex availability: the 2014 wave is the first to provide systematic regional coverage of mobile money behavioural indicators. The end year reflects the most recent period for which the World Development Indicators and the World Bank Entrepreneurship Database provide sufficient coverage of the variables used in the analysis (Klapper et al., 2025; World Bank, 2024).

Two countries are excluded. Zimbabwe is omitted because recurrent currency instability and hyperinflationary episodes generate macroeconomic observations that are not comparable with the rest of the panel and would distort within-country fixed-effects estimation. Sierra Leone is excluded because of irregularities in the new business density series. Appendix A.4 provides the detailed rationale for both exclusions.

The dependent variable is new business density, obtained from the World Bank Entrepreneurship Database indicator IC.BUS.NDNS.ZS, defined as the number of newly registered formal corporations per 1,000 working-age adults. Because some observations take very low or zero values, the variable is transformed as $\ln(1 + \text{NBD}_{it})$, where NBD_{it} denotes new business density in country i and year t .

The principal explanatory variable is a composite FinTech ecosystem index constructed from demand-side and supply-side indicators. Demand-side indicators, drawn from the Global Findex Database, capture behavioural adoption of formal and digital financial services. Supply-side indicators, drawn from the World Development Indicators, capture the infrastructure required for digital financial services to operate at scale. The construction of both sub-indices and the composite measure is described in Section 3.2. The time-varying controls are the natural logarithm of GDP per capita in constant 2015 US dollars, consumer price inflation, and trade openness measured as exports plus imports of goods and services as a percentage of GDP, all from the World Development Indicators. The moderating variables are private credit to GDP and broad money to GDP, also from the World Development Indicators.

3.2 Construction of the FinTech Ecosystem Index

The FinTech ecosystem index is constructed through a two-stage principal component analysis: first, it produces separate demand-side and supply-side sub-indices, and then combines the standardised sub-indices into a composite measure. PCA is appropriate because the underlying indicators are correlated measures of a latent ecosystem construct, and the approach is consistent with established practice in constructing financial inclusion and digital finance indices (Chinoda & Kapingura, 2023; Kamara & Yu, 2024). The two-stage structure offers three advantages over a single-stage composite: it accommodates the different measurement frequencies of the input data, with Findex demand-side indicators observed at discrete survey waves and WDI supply-side indicators observed annually; it enables direct decomposition of the composite index into demand and supply channels, which is the basis for the empirical test of Hypothesis 2; and it preserves the conceptual distinction between behavioural adoption and infrastructural provision that the ecosystem framework in Section 2 motivates.

Stage 1: Supply-side sub-index. The supply sub-index is constructed by applying PCA to the four WDI infrastructure indicators in Table 1: internet use, mobile cellular subscriptions, fixed broadband subscriptions,

and electricity access. Each indicator is standardised to a mean of 0 and a standard deviation of 1 prior to extraction. The first principal component is retained and sign-anchored on internet use, the foundational connectivity indicator, so that higher values correspond to stronger digital infrastructure. The first component explains 72.7 per cent of the variance across the four standardised indicators. The resulting component is denoted $Supply_{it}$.

Stage 1: Demand-side sub-index. The demand sub-index is constructed from Findex behavioural indicators capturing account ownership, digital payment use, mobile money saving, mobile money borrowing, and related forms of digital financial use. Because Findex variables are observed at discrete survey waves rather than annually, PCA is applied separately within each wave. Indicators are standardised within wave, and the first principal component is extracted, with its sign anchored in mobile money account ownership, the primary behavioural indicator of digital financial adoption. Across waves, the first component accounts for the dominant share of the common variation in the demand-side indicators. Wave-specific PCA scores are then projected onto annual observations through period-score replication: the 2014 wave score is assigned to 2014–2016, the 2017 wave score to 2017–2019, and the 2021 wave score to 2020–2022. This procedure preserves the discrete-wave structure of the underlying data and avoids imposing artificial annual variation through linear interpolation. The resulting annual demand sub-index is denoted $Demand_{it}$.

Stage 2: Composite ecosystem index. The second stage combines the demand and supply sub-indices. Both sub-indices are first standardised on the estimation sample:

$$Demand_z_{it} = \frac{Demand_{it} - \mu_{Demand}}{\sigma_{Demand}}$$

$$Supply_z_{it} = \frac{Supply_{it} - \mu_{Supply}}{\sigma_{Supply}}$$

PCA is then applied to the two standardised sub-indices. The first principal component is retained and sign-anchored on $Demand_z_{it}$. It explains 79.1 per cent of the variance in the two-dimensional input space and correlates strongly with both sub-components: $r = 0.91$ with the demand-side sub-index and $r = 0.86$ with the

supply-side sub-index. The resulting composite index is denoted FNT_ECO_{it} and serves as the principal regressor in the baseline specification.

Table 3 reports the loadings and variance shares from the index-construction procedure.

Table 3. Construction of the FinTech Ecosystem Index

Panel A. Stage 1 supply-side sub-index

Indicator	Loading on PC1	Coverage
Individuals using the internet, % of population [IT.NET.USER.ZS]	0.538	0.98
Access to electricity, % of population [EG.ELC.ACCS.ZS]	0.522	1.00
Mobile cellular subscriptions, per 100 people [IT.CEL.SETS.P2]	0.505	1.00
Fixed broadband subscriptions, per 100 people [IT.NET.BBND.P2]	0.429	0.98

Note: PC1 explains 72.7 per cent of the variance across the four standardised supply-side indicators. The sign is anchored on internet use.

Panel B. Stage 1 demand-side sub-index, illustrative wave: 2017–2019

Indicator	Loading on PC1	Coverage
Account ownership	0.386	1.00
Made or received a digital payment	0.386	1.00
Received a digital payment	0.385	1.00
Made a digital payment	0.379	1.00
Used a mobile phone or the internet to pay bills	0.344	1.00

Indicator	Loading on PC1	Coverage
Mobile money account ownership	0.330	0.91
Financial institution account ownership	0.327	1.00
Saved using mobile money	0.277	1.00

Note: PC1 explains 81.5 per cent of the variance for the 2017–2019 wave. Across the Findex waves, PC1 variance shares range from 70.7 to 96.4 per cent. The sign is anchored on mobile money account ownership.

Panel C. Stage 2 composite ecosystem index

Sub-index	Loading on PC1
Demand sub-index, standardised	0.755
Supply sub-index, standardised	0.656

Note: PC1 explains 79.1 per cent of the variance in the two-dimensional input space. The sign is anchored on the standardised demand sub-index.

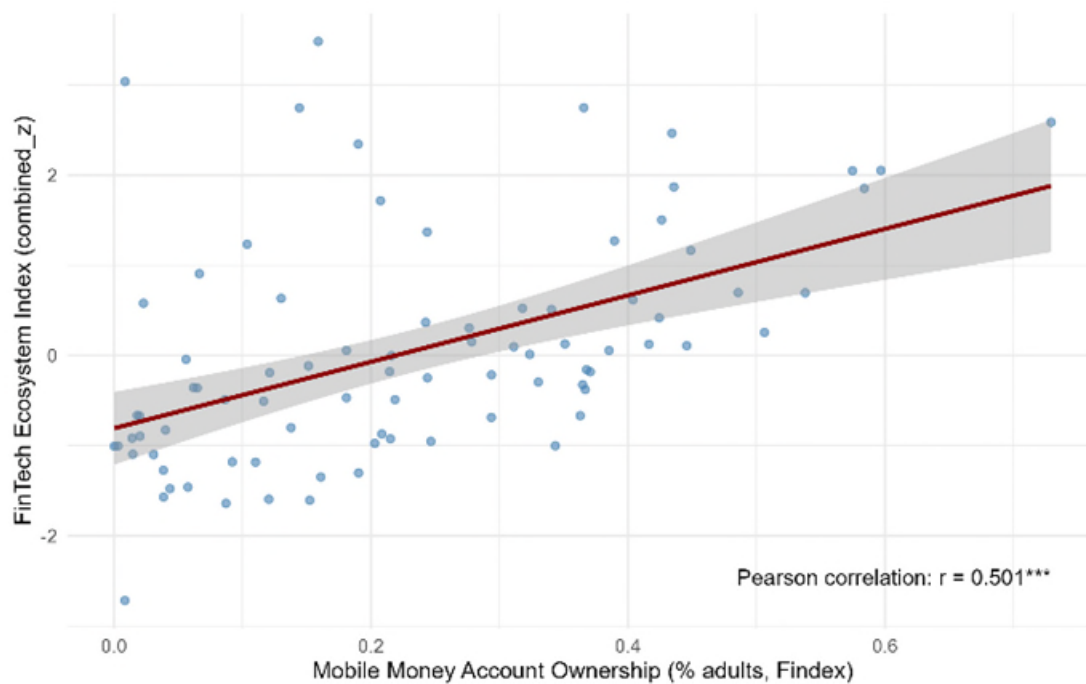
3.3 External Validation of the Composite Index

External validation addresses a central concern in composite-index construction: whether the index captures the intended concept rather than unrelated common variation among its indicators. This concern is particularly relevant in financial inclusion and FinTech research, where composite indices can be sensitive to indicator selection, scaling, and aggregation choices (Ahmad et al., 2020; Ha et al., 2025). Three criteria guide the validation. First, the composite index should correlate positively with a recognised benchmark of digital financial adoption; mobile money account ownership serves this role because it is the most direct cross-country measure of digital financial service adoption in the region and is widely used in the African digital finance literature (Ahmad et al., 2020; Osabutey & Jackson, 2024). Second, the demand sub-index should correlate more strongly with this benchmark than the composite index does, since it directly captures behavioural use while the

composite also incorporates infrastructural variation. Third, the composite index should remain strongly correlated with both constituent sub-indices, confirming that the second-stage extraction preserves meaningful information from both demand and supply dimensions rather than collapsing them.

The results support the index's validity across all three criteria. The composite FinTech ecosystem index correlates with mobile money account ownership at $r = 0.501$ across the Findex anchor-year validation sample ($N = 84$; $p < 0.001$), as shown in Figure 1. Consistent with the second criterion, the demand sub-index correlates more strongly with mobile money account ownership ($r = 0.575$), reflecting its direct grounding in behavioural adoption indicators. The composite index also maintains high internal consistency with both constituent dimensions, correlating at $r = 0.91$ with the demand sub-index and $r = 0.86$ with the supply sub-index, indicating that the second-stage extraction integrates the two dimensions without material loss of information. Taken together, these patterns support the interpretation of FNT_ECO_{it} as a defensible national-level measure of FinTech ecosystem development.

Figure 1. External Validation of the Composite FinTech Ecosystem Index



Note: Figure 1 plots the relationship between the composite FinTech ecosystem index and mobile money account ownership in Findex anchor years. The fitted line illustrates the positive association between the constructed index and the benchmark adoption indicator.

3.4 Baseline Specification and Estimator Choice

The baseline empirical specification estimates the association between FinTech ecosystem development and formal entrepreneurial entry using a two-way fixed-effects model:

$$\ln(1 + NBD_{it}) = \alpha_i + \lambda_t + \beta_1 FNT_ECO_{it} + X'_{it}\theta + \varepsilon_{it} \quad (1)$$

where i indexes countries and t indexes years. The term α_i denotes country fixed effects, λ_t denotes year fixed effects, FNT_ECO_{it} is the composite FinTech ecosystem index, X_{it} is the vector of time-varying controls, and ε_{it} is the idiosyncratic error term. The coefficient of interest, β_1 , captures the within-country association between FinTech ecosystem development and the log of one plus new business density, conditional on macroeconomic controls and common time shocks.

Two-way fixed effects are preferred because they absorb time-invariant heterogeneity across countries, including geography, legal origin, colonial history, institutional inheritance, and persistent differences in business formation. Although the Hausman specification test does not reject the random-effects estimator ($\chi^2 = 0.48, df = 4, p = 0.98$), fixed effects provide a more conservative design for estimating within-country changes over time (Hausman, 1978).

Standard errors are computed using the Driscoll–Kraay covariance estimator with a maximum lag of two. This approach is robust to heteroskedasticity, serial correlation, and general forms of cross-sectional dependence (Driscoll & Kraay, 1998). Although the Pesaran cross-sectional dependence test does not reject the null of cross-sectional independence in the baseline residuals ($CD = 0.77, p = 0.44$), Driscoll–Kraay standard errors are retained as a conservative inference procedure (Pesaran, 2021).

Collinearity diagnostics are conducted for the moderation models. The correlation between private credit depth and broad monetary depth is substantial, but variance inflation diagnostics remain within conventional

thresholds. Ordinary variance inflation factors in the main-effects specification range from 1.24 to 4.15. Generalised variance inflation factors for the joint moderation specification, computed following Fox and Monette (1992), yield scaled values between 1.17 and 2.20, below the corresponding threshold of $\sqrt{5} \approx 2.24$. These diagnostics indicate that collinearity does not prevent separate interpretation of the two interaction terms.

3.5 Channel Decomposition

To test Hypothesis 2, the baseline model is re-estimated by replacing the composite index with the two standardised sub-indices:

$$\ln(1 + NBD_{it}) = \alpha_i + \lambda_t + \beta_D Demand_z_{it} + \beta_S Supply_z_{it} + X'_{it}\theta + \varepsilon_{it} \quad (2)$$

where $Demand_z_{it}$ and $Supply_z_{it}$ denote the standardised demand-side and supply-side sub-indices. The coefficient β_D estimates the association between behavioural adoption and formal entrepreneurial entry, while β_S estimates the corresponding association for infrastructure provision, conditional on adoption.

Because both sub-indices are standardised, the coefficients are comparable across channels. Demand-only and supply-only specifications are also estimated to assess whether the isolated channel estimates differ from the conditional estimates obtained when both dimensions are included simultaneously in the model.

3.6 Moderation Specification and Marginal Effects

To test Hypotheses 3 and 4, the baseline model is augmented with private credit depth, broad monetary depth, and their interactions with the FinTech ecosystem index:

$$\ln(1 + NBD_{it}) = \alpha_i + \lambda_t + \beta_1 FNT_ECO_{it} + \beta_2 CRD_{it} + \beta_3 BM_{it} + \gamma_1 (FNT_ECO_{it} \times CRD_{it}) + \gamma_2 (FNT_ECO_{it} \times BM_{it}) + X'_{it}\theta + \varepsilon_{it} \quad (3)$$

where CRD_{it} denotes private credit to GDP and BM_{it} denotes broad money to GDP. Both moderators are mean-centred on the estimation sample. This centring allows β_1 to be interpreted as the marginal association between FinTech ecosystem development and formal entrepreneurial entry, holding credit depth and broad monetary depth at their sample means.

The marginal effect of the FinTech ecosystem index is:

$$\frac{\partial \ln(1 + NBD_{it})}{\partial FNT_ECO_{it}} = \beta_1 + \gamma_1 CRD_{it} + \gamma_2 BM_{it} \quad (4)$$

To interpret the monetary-depth interaction, the marginal effect is computed at selected percentiles of the broad-money distribution while holding private credit at its sample mean. The zero-crossing point is obtained by setting the marginal effect equal to zero and solving for BM :

$$BM^* = -\frac{\beta_1}{\gamma_2} \quad (5)$$

The position of BM^* relative to the empirical support of broad money determines the interpretation of the interaction. If BM^* lies outside the observed range, the interaction indicates attenuation without reversal. If BM^* lies within the observed range, the interaction indicates attenuation with localised reversal. This distinction is important because interaction coefficients alone do not reveal whether the focal effect merely weakens or changes sign within the observed sample, a problem widely noted in methodological discussions of moderation effects (Assaf et al., 2020; Baranger et al., 2023; Becker et al., 2018).

3.7 Identification Diagnostics

The principal identification concern is reverse causality: increases in formal entrepreneurial entry may attract FinTech investment or accelerate digital financial service provision, generating contemporaneous correlation between FNT_ECO_{it} and $\ln(1 + NBD)_{it}$ that does not reflect a causal effect of FinTech ecosystem development on entry. Because the analysis relies on observational panel data, the empirical strategy is framed as diagnostic triangulation rather than definitive causal identification. Four diagnostics assess whether the evidence is consistent with a directional interpretation from FinTech ecosystem development to formal entrepreneurial entry.

The first diagnostic is a Hausman–Wu endogeneity test that compares the two-way fixed-effects estimator with an instrumental-variable fixed-effects estimator using the one-period lag of FNT_ECO_{it} as an instrument for the contemporaneous index. Under the null of conditional exogeneity, both estimators are consistent, but the fixed-effects estimator is more efficient; a statistically significant difference would indicate that the contemporaneous FinTech ecosystem index is endogenous (Hausman, 1978; Wu, 1973).

The second diagnostic is a control-function test. The first-stage residual from a regression of FNT_ECO_{it} on its lag and exogenous covariates is added to the structural equation; a statistically significant coefficient on this residual indicates endogeneity of the contemporaneous regressor, whereas an insignificant coefficient is consistent with conditional exogeneity.

The third diagnostic examines temporal ordering through lag specifications. The baseline equation is re-estimated, replacing contemporaneous FNT_ECO_{it} with its one-period and two-period lags. If FinTech ecosystem development precedes formal entry, lagged values should predict subsequent new business density with a pattern that attenuates at longer lags, consistent with a short-run access or transaction-cost mechanism rather than slow-building reverse causation.

The fourth diagnostic is a reverse-prediction placebo that uses contemporaneous formal entrepreneurial entry to predict next-period FinTech ecosystem development. A significant coefficient would be consistent with reverse or bidirectional adjustment, though this diagnostic requires cautious interpretation because shared country-specific trends can generate positive reverse-prediction coefficients even in the absence of a direct reverse-causal mechanism.

As supporting evidence, dynamic panel estimates are reported using the system generalised method of moments. The specification includes the lagged dependent variable, instruments, potentially endogenous regressors with internal lags, and collapses the instrument matrix to limit proliferation. Arellano–Bond serial correlation tests and overidentification tests assess the validity of the dynamic specification (Arellano & Bover, 1995; Blundell & Bond, 1998). These estimates complement the four primary diagnostics but are not the principal identification strategy.

4. Empirical Results

4.1 Descriptive Statistics and Ecosystem Evolution

Table 2 reports descriptive statistics for the dependent variable, the composite FinTech ecosystem index, its demand- and supply-side sub-components, the two moderators, and the time-varying controls. The dependent variable, $\ln(1 + NBD)$, has a mean of 0.77 and a standard deviation of 0.75, indicating substantial variation in

formal entrepreneurial entry across the sample. The composite FinTech ecosystem index has a mean close to zero and a standard deviation of 1.27, consistent with its construction as a principal-component-based measure. The demand- and supply-side sub-indices also exhibit considerable dispersion, suggesting meaningful cross-country heterogeneity in both behavioural adoption and infrastructural provision.

The two moderators show substantial variation across the sample. Private credit averages 22.85 per cent of GDP, while broad money averages 36.34 per cent of GDP. The broad-money distribution is especially dispersed, ranging from 10.72 to 176.79 per cent of GDP. This variation provides the empirical basis for examining whether the FinTech–entry relationship differs across macro-financial environments, as implied by the credit-segmentation and monetary-substitution arguments developed in Section 2.5.

Table 2. Descriptive Statistics

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Log(1 + new business density)	266	0.77	0.75	0.01	0.20	0.57	0.99	3.18
FNT_ECO, composite ecosystem index	237	0.07	1.27	−2.72	−0.90	−0.18	0.63	3.48
Demand sub-index, standardised	246	0.03	1.10	−2.66	−0.76	−0.13	0.57	3.19
Supply sub-index, standardised	402	0.15	1.04	−1.34	−0.60	0.00	0.57	4.23
Private credit, % GDP	372	22.85	22.02	0.00	11.77	15.80	24.58	128.84
Broad money, % GDP	363	36.34	23.78	10.72	22.35	28.37	42.19	176.79
GDP per capita, constant 2015 USD	398	2,338	3,125	254	689	1,126	2,228	19,481
CPI inflation, annual %	387	9.98	30.98	−6.69	1.72	4.41	8.34	380.00
Trade openness, % GDP	359	69.11	33.44	2.70	45.27	60.91	85.52	213.35

Note: The initial country–year frame contains 414 observations across 46 Sub-Saharan African economies from 2014 to 2022. Zimbabwe and Sierra Leone are excluded. The N column reports variable-specific availability before model-specific complete-case restrictions are applied. FNT_ECO is the first principal component of the standardised demand and supply sub-indices.

Figure 2 shows the temporal evolution of the composite FinTech ecosystem index. The cross-country mean rises modestly over the study period, while dispersion across countries remains substantial. The individual country trajectories display stepwise changes around Findex update years, reflecting the period-score replication of the demand-side sub-index. At the same time, within-period variation is mainly driven by annual supply-side infrastructure indicators from the World Development Indicators. The figure, therefore, illustrates both gradual regional improvement and persistent cross-country heterogeneity in FinTech ecosystem development.

Figure 2. Evolution of the Composite FinTech Ecosystem Index, 2014–2022

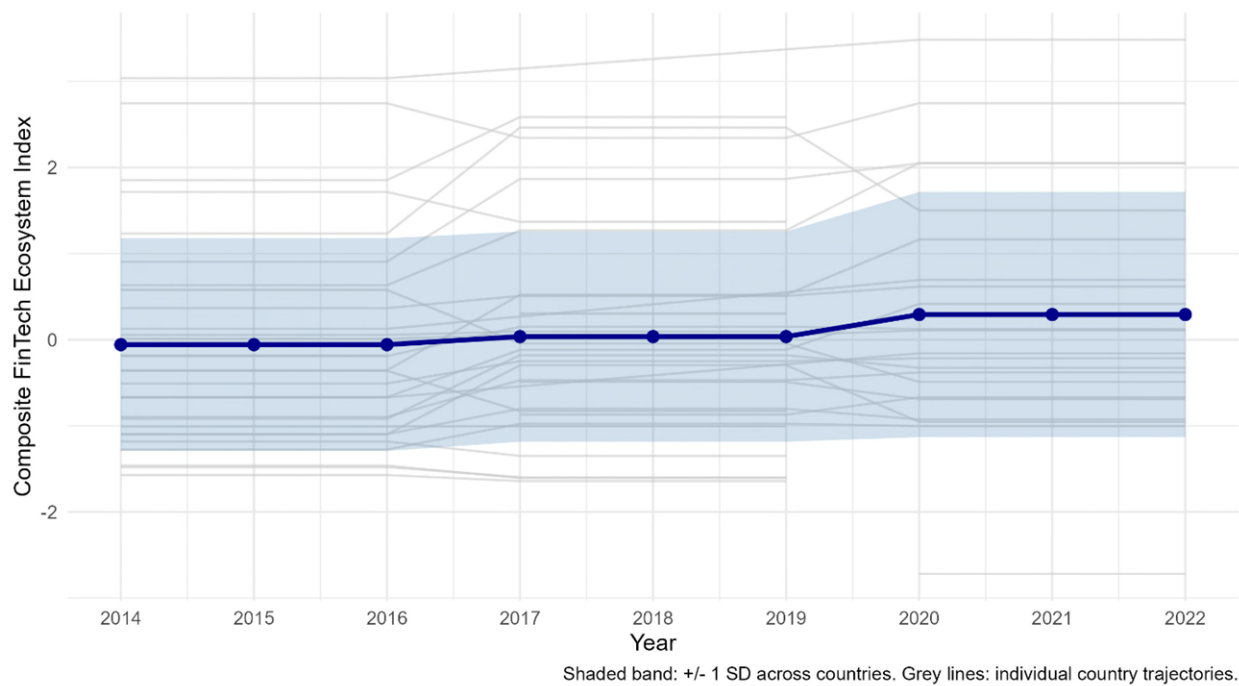


Table 4 reports pairwise correlations among the main regression variables. The composite FinTech ecosystem index is strongly correlated with both the demand-side and supply-side sub-indices, confirming that the second-stage index preserves information from both ecosystem dimensions. The correlation between private credit and

broad money is also high, at 0.750, which justifies estimating a joint moderation specification rather than interpreting credit and monetary depth in isolation.

Table 4. Pairwise Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) $\ln(1 + NBD)$	1.000								
(2) FNT_ECO	0.790	1.000							
(3) Demand sub-index	0.666	0.922	1.000						
(4) Supply sub-index	0.746	0.861	0.597	1.000					
(5) CRD, centred	0.719	0.718	0.594	0.647	1.000				
(6) BM, centred	0.696	0.665	0.477	0.662	0.750	1.000			
(7) Log GDPpc	0.572	0.793	0.551	0.798	0.538	0.559	1.000		
(8) Inflation	-0.075	-0.070	-0.021	-0.126	-0.140	-0.013	-0.078	1.000	
(9) Trade openness	0.382	0.248	0.034	0.534	0.267	0.505	0.659	-0.199	1.000

Note: Pearson correlations are reported for the available estimation sample. CRD denotes private credit to GDP, mean-centred. BM denotes broad money to GDP, mean-centred.

4.2 Baseline Results and Hypothesis 1

Table 5 reports the baseline and moderation estimates. Column (1) presents the two-way fixed-effects estimate of the baseline specification. The coefficient on the composite FinTech ecosystem index is positive and statistically significant. A one-standard-deviation increase in FNT_ECO is associated with a 0.182 increase in $\ln(1 + NBD)$, conditional on country fixed effects, year fixed effects, and time-varying macroeconomic

controls. This result supports Hypothesis 1, which predicts a positive association between FinTech ecosystem development and formal entrepreneurial entry.

Among the controls, trade openness is positive and statistically significant, suggesting that integration with external markets is associated with higher formal entry. GDP per capita and inflation are not statistically significant in the baseline specification, even after including country- and year-fixed effects. This pattern is consistent with a within-country design in which country fixed effects absorb persistent cross-country differences in income levels and macroeconomic structure.

Table 5. Baseline and Moderation Results

Variable	(1) Baseline	(2) Isolated CRD	(3) Isolated BM	(4) Joint
FNT_ECO	0.182*** (0.023)	0.225*** (0.037)	0.196*** (0.021)	0.186*** (0.031)
CRD, mean-centred	—	0.001 (0.003)	—	−0.007** (0.003)
BM, mean-centred	—	—	0.002 (0.006)	0.007 (0.006)
FNT_ECO × CRD	—	−0.001 (0.002)	—	0.001 (0.001)
FNT_ECO × BM	—	—	−0.002 (0.001)	−0.003*** (0.001)
Log GDP per capita	−0.000	−0.000	−0.000	−0.000

Variable	(1) Baseline	(2) Isolated CRD	(3) Isolated BM	(4) Joint
	(0.000)	(0.000)	(0.000)	(0.000)
Inflation	−0.004	−0.005*	−0.006**	−0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Trade openness	0.005***	0.005***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	414	414	414	414
Countries	46	46	46	46

Note: Dependent variable: $\ln(1 + NBD)$. Two-way fixed-effects estimates with Driscoll–Kraay standard errors in parentheses, using max-lag = 2. CRD and BM are mean-centred on the estimation sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimated magnitude is economically meaningful. A coefficient of 0.182 implies that within-country improvements in FinTech ecosystem development are associated with non-trivial increases in formal entry. For comparison, prior studies show that entry-barrier reforms can increase firm entry, that formalisation reforms can substantially raise MSME registration, that financial development is associated with higher new business density in African economies, and that country-level economic conditions are strongly related to FinTech start-up formation (Assenova, 2021; Haddad & Hornuf, 2018; Klapper et al., 2006; Munemo, 2018). In the present sample, a 0.4 standard-deviation increase in the composite ecosystem index, approximately equal to the within-country gain observed in the median economy over the study period, corresponds to an increase of about 0.073 in $\ln(1 + NBD)$. The magnitude is therefore consistent with the interpretation that FinTech ecosystems can

contribute meaningfully to formal business formation, while the observational design warrants caution in causal interpretation.

4.3 Channel Decomposition and Hypothesis 2

Table 6 decomposes the composite FinTech ecosystem index into its demand- and supply-side components. The demand-only specification in column (1) shows a positive and statistically significant association between demand-side adoption and formal entrepreneurial entry. A one-standard-deviation increase in the demand sub-index is associated with a 0.149 increase in $\ln(1 + NBD)$.

The supply-only specification in column (2) yields a negative coefficient on the supply-side sub-index, significant at the 10 per cent level. When both sub-indices are included jointly in column (3), the demand-side coefficient remains positive and statistically significant, while the supply-side coefficient becomes more negative and statistically significant at the 5 per cent level. This pattern supports Hypothesis 2: the positive FinTech–entry association is driven primarily by behavioural adoption, while infrastructure provision alone does not appear to generate the same entry-enhancing association.

Table 6. Channel Decomposition

Variable	(1) Demand only	(2) Supply only	(3) Joint
Demand sub-index, z	0.149*** (0.014)	—	0.161*** (0.016)
Supply sub-index, z	—	−0.223* (0.121)	−0.236** (0.105)
Log GDP per capita	−0.000 (0.000)	0.000** (0.000)	0.000 (0.000)

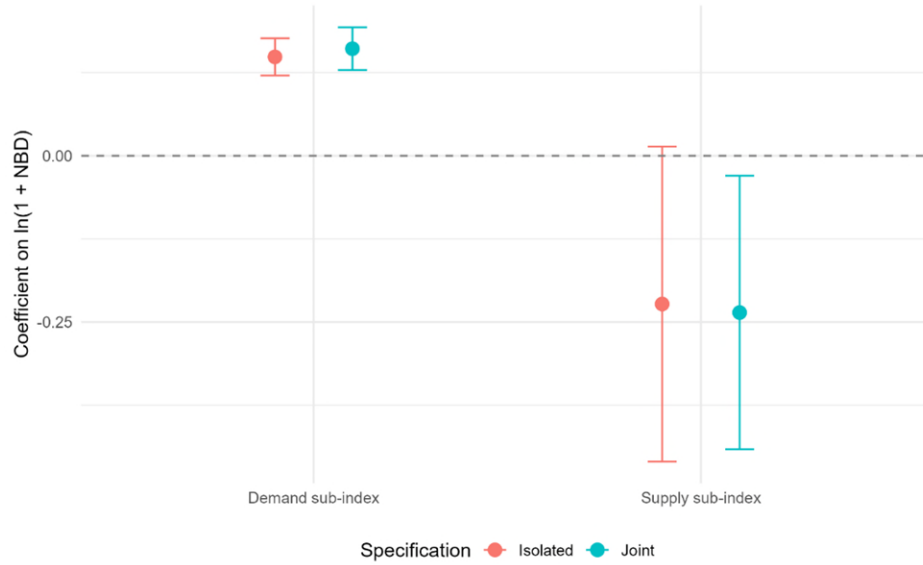
Variable	(1) Demand only	(2) Supply only	(3) Joint
Inflation	−0.004 (0.003)	−0.002 (0.002)	−0.004 (0.002)
Trade openness	0.005*** (0.001)	0.004* (0.002)	0.005*** (0.001)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	414	414	414
Countries	46	46	46

Note: Dependent variable: $\ln(1 + NBD)$. The demand and supply sub-indices are standardised to have a mean of 0 and a standard deviation of 1. Two-way fixed-effects estimates with Driscoll–Kraay standard errors in parentheses, using max-lag = 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3 visualises the demand–supply asymmetry by plotting coefficient estimates and 95 per cent confidence intervals for the isolated and joint channel specifications. The demand-side coefficient is consistently positive and precisely estimated. The supply-side coefficient is consistently negative, though less precisely estimated in the supply-only model. The joint specification indicates that infrastructure is negatively associated with formal entry, holding behavioural adoption constant.

The results indicate that infrastructure expansion alone does not necessarily broaden entrepreneurial opportunity. In the absence of corresponding behavioural adoption, such expansion may disproportionately benefit actors already capable of exploiting digital channels. This pattern aligns with firm-level evidence showing that digital financial tools generate stronger productivity effects when integrated with traditional financial services and organisational capabilities (Konte & Tetteh, 2023).

Figure 3. Demand–Supply Channel Decomposition



4.4 Moderation Analysis and Hypotheses 3 and 4

Columns (2) to (4) of Table 5 examine whether the FinTech–entry relationship varies with private credit depth and broad monetary depth. Column (4), which includes both moderators and both interaction terms, is the preferred specification because private credit and broad money are strongly correlated.

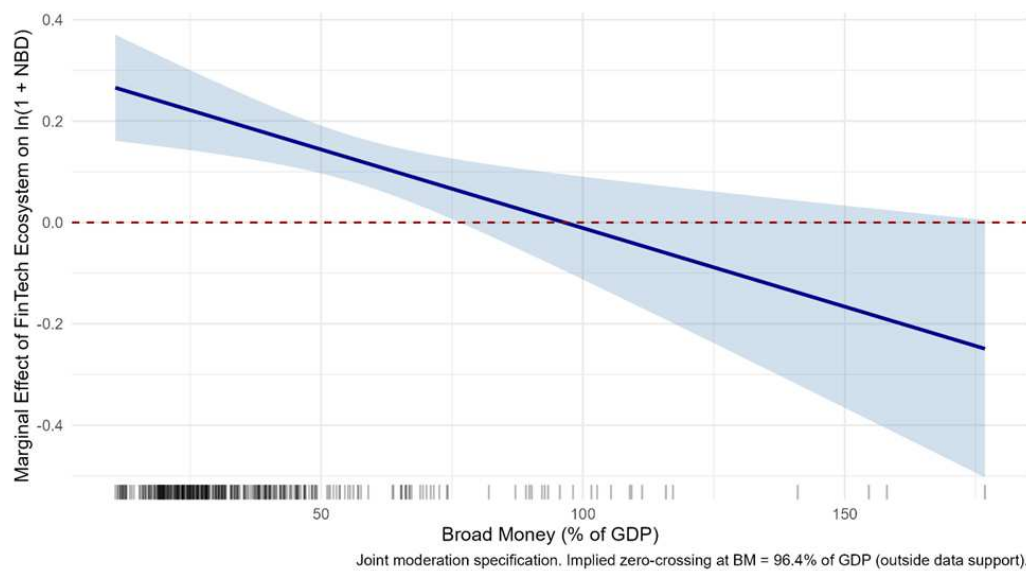
Hypothesis 3 predicts that private credit depth does not significantly moderate the relationship between FinTech ecosystem development and formal entrepreneurial entry. The joint specification supports this prediction. The interaction between *FNT_ECO* and private credit is small and statistically insignificant ($\gamma_1 = 0.001, SE = 0.001, p = 0.45$). This finding is consistent with the segmentation argument developed in Section 2.5: aggregate private credit may primarily capture lending to firms already integrated into the formal banking system rather than marginal credit availability for prospective entrants (Beck et al., 2019).

Hypothesis 4 predicts that broad monetary depth negatively moderates the FinTech–entry relationship. The evidence supports this prediction. In the joint specification, the interaction between *FNT_ECO* and broad money is negative and statistically significant ($\gamma_2 = -0.003, SE = 0.001, p = 0.004$). This indicates that the positive association between FinTech ecosystem development and formal entry weakens as broad monetary depth

increases. The result is consistent with a partial-substitution mechanism: where conventional monetary systems already provide payment, savings, and liquidity-management services, the marginal contribution of additional FinTech ecosystem development is smaller (Klapper & Love, 2010; Klapper et al., 2014; Beck et al., 2019).

Figure 4 illustrates this moderation pattern by plotting the marginal effect of *FNT_ECO* across the broad-money distribution, holding private credit at its mean. The marginal effect declines monotonically as broad money rises. It remains positive and statistically significant across most of the distribution, but becomes statistically indistinguishable from zero in the upper tail.

Figure 4. Marginal Effect of FinTech Ecosystem Development Across Broad Monetary Depth



The zero-crossing calculation from equation (5) yields an estimated threshold of approximately 96.4 per cent of GDP. This is the level of broad money at which the implied marginal association between *FNT_ECO* and $\ln(1 + NBD)$ equals zero, holding private credit at its mean. The interaction term is negative in the upper tail of the broad-money distribution but remains within the sample's observed range. Accordingly, the marginal association between FinTech ecosystem development and formal entry weakens at high levels of broad money, but it does not turn negative across most country-year observations. The weakening is economically meaningful only among the most monetarily developed observations in the sample.

4.5 Identification Diagnostics

The identification diagnostics provide evidence consistent with a directional link from FinTech ecosystem development to formal entrepreneurial entry. Because the analysis relies on observational panel data, these diagnostics do not establish causality.

The Hausman–Wu test compares the fixed-effects baseline estimate with an instrumental-variable fixed-effects estimate using the one-period lag of *FNT_ECO* as an instrument for the contemporaneous index (Wu, 1973; Hausman, 1978). The test statistic is $\chi^2 = 1.76$, with $p = 0.78$, so the null of conditional exogeneity is not rejected. The fixed-effects estimate of 0.182 and the instrumental-variable estimate of 0.204 are statistically similar.

The control-function diagnostic yields the same conclusion. The coefficient on the first-stage residual is -0.027 , with a standard error of 0.049 and $p = 0.58$. The residual term is therefore not statistically significant, providing no evidence that the contemporaneous FinTech ecosystem index is endogenous conditional on the fixed effects and controls.

The temporal lag specifications provide additional support for a short-run directional interpretation. The one-period lag of *FNT_ECO* is positive and statistically significant ($\beta = 0.120, SE = 0.036, p = 0.001$), while the two-period lag is statistically insignificant and negative ($\beta = -0.045, SE = 0.051, p = 0.37$). This pattern suggests that the association between ecosystem development and formal entry is concentrated in the contemporaneous-to-one-year window rather than accumulating as a slow-moving stock effect.

The reverse-prediction placebo yields a positive and statistically significant coefficient when contemporaneous business density is used to predict the next period *FNT_ECO*. This result cautions against a strictly one-directional causal interpretation. However, it is also consistent with shared country-specific trends in FinTech development and business formalisation over the sample period. Taken together, the Hausman–Wu test, control-function diagnostic, lag structure, and reverse-prediction placebo suggest that the relationship is unlikely to be driven solely by reverse causality, although bidirectional adjustment cannot be ruled out.

Table 7 reports further identification and robustness checks. The system GMM estimates are positive and similar in magnitude to the fixed-effects baseline, although less precisely estimated. The lagged dependent variable is

positive and statistically significant, indicating persistence in formal entrepreneurial entry. The Arellano–Bond second-order serial correlation tests do not indicate second-order serial correlation, and the Sargan tests do not reject the overidentifying restrictions, supporting the validity of the dynamic specification (Arellano & Bover, 1995; Blundell & Bond, 1998). Additional robustness checks show that the baseline coefficient is unchanged after winsorising controls and excluding hyperinflationary observations. The lag and balanced-core specifications also preserve the positive association, although the magnitude is smaller in the balanced-core sample.

Overall, the diagnostics are consistent with a positive directional relationship between FinTech ecosystem development and formal entrepreneurial entry. The observational panel design, however, does not permit definitive causal inference.

Table 7. Identification Robustness

Variable	(1) SYS-GMM	(2) GMM + CRD	(3) Winsorised	(4) Excl. hyperinf.	(5) Lag-1	(6) Lag-2	(7) Balanced core
FNT_ECO	0.144	0.162*	0.182***	0.182***	—	—	0.076***
	(0.088)	(0.087)	(0.023)	(0.023)			(0.027)
Lag-1 FNT_ECO	—	—	—	—	0.120***	—	—
					(0.036)		
Lag-2 FNT_ECO	—	—	—	—	—	−0.045	—
						(0.051)	
Lagged DV, ln(1+NBD)	0.682***	0.669***	—	—	—	—	—
	(0.149)	(0.103)					
CRD, mean-centred	—	0.000	—	—	—	—	—
		(0.004)					
Log GDP per capita	0.000	−0.000	−0.000	−0.000	−0.000	0.000	0.000***

Variable	(1) SYS-GMM	(2) GMM + CRD	(3) Winsorised	(4) Excl. hyperinf.	(5) Lag-1	(6) Lag-2	(7) Balanced core
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Inflation	−0.000	0.001	−0.004	−0.004	−0.003	0.000	−0.005
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Trade openness	0.003**	0.003***	0.005***	0.005***	0.005**	0.002	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
AR(2) p-value	0.51	0.52	—	—	—	—	—
Sargan p-value	0.29	0.10	—	—	—	—	—
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Observations	322	322	414	414	368	322	351
Countries	46	46	46	46	46	46	39

Note: Dependent variable: $\ln(1 + NBD)$, except columns (5) and (6), which use lagged values of the composite FinTech ecosystem index. Columns (1) and (2) report two-step system GMM estimates with a collapsed instrument matrix and Windmeijer-corrected standard errors. Columns (3) to (7) report two-way fixed-effects estimates with Driscoll–Kraay standard errors in parentheses, using max-lag = 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.6 Robustness to Sample and Measurement Variation

Table 8 reports three additional checks that assess whether the baseline association is sensitive to influential economies, the measurement of entrepreneurial entry, or the temporal construction of the demand-side sub-index.

The first specification excludes South Africa, the largest and most financially developed economy in the sample. The coefficient on the composite index remains positive and statistically significant, rising from the baseline estimate of 0.182 to 0.224, indicating that South Africa does not drive the baseline association and, if anything, is stronger among the remaining economies.

The second specification replaces new business density with the log of one plus the raw count of new business registrations. The coefficient remains positive and statistically significant, with a larger point estimate of 0.307. The increase in magnitude is consistent with the density measure imposing a stricter population-adjusted test of the FinTech–entry relationship, rather than reflecting any instability in the underlying association.

The third specification restricts the sample to Findex anchor years, 2014, 2017, and 2021, to address the concern that period-score replication of the demand sub-index introduces artificial persistence or within-window measurement artefacts. The coefficient remains positive and statistically significant, though smaller in magnitude at 0.137. The reduction is expected: the anchor-year specification uses fewer observations and removes within-window annual variation arising from the interaction between replicated demand scores and annually observed supply-side indicators. The result, therefore, confirms that the positive association between FinTech ecosystem development and formal entrepreneurial entry is not an artefact of the period-replication procedure.

Taken together with the identification and robustness checks in Table 7, these results establish that the main finding is stable across alternative samples, alternative dependent-variable measurement, and a more conservative treatment of Findex wave timing.

Table 8. Sample and Measurement Robustness

Variable	(1) Excl. ZAF	(2) Alt. DV: $\ln(1+nreg)$	(3) Findex anchors only
FNT_ECO	0.224*** (0.031)	0.307*** (0.056)	0.137*** (0.015)
Log GDP per capita	−0.000 (0.000)	0.000** (0.000)	−0.000 (0.000)
Inflation	−0.003 (0.003)	−0.004 (0.006)	0.001 (0.002)
Trade openness	0.005*** (0.001)	0.006* (0.003)	0.009*** (0.002)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	405	414	138
Countries	45	46	46

Note: Dependent variable: $\ln(1 + NBD)$, except in column (2), where the dependent variable is $\ln(1 + \text{new business registrations})$. All specifications include country and year fixed effects. Driscoll–Kraay standard errors are reported in parentheses, using max-lag = 2. Column (1) excludes South Africa. Column (3) restricts the sample to Findex anchor years: 2014, 2017, and 2021. *p < 0.10, **p < 0.05, ***p < 0.01.

5. Discussion, Implications, and Conclusion

5.1 Demand-Side Adoption and the Limits of Infrastructure-Led FinTech Development

Demand-side adoption, not infrastructure, drives the positive association between FinTech ecosystem development and formal entrepreneurial entry. The demand sub-index is positively associated with formal entry ($\beta_D = 0.161, p < 0.001$), whereas the supply sub-index is negatively associated with entry, controlling for adoption ($\beta_S = -0.236, p = 0.026$).

This asymmetry reflects a fundamental distinction between technical possibility and economic use. Infrastructure creates the conditions under which digital financial services can operate, but adoption determines whether those services become economically meaningful for prospective entrepreneurs. Mobile connectivity, broadband access, and electricity can support digital payments, digital savings, and transaction records only when users have the capabilities, trust, incentives, and institutional support required to use them. This interpretation is consistent with ecosystem perspectives that emphasise the co-evolution of infrastructure, institutions, intermediaries, and users in shaping entrepreneurial outcomes (Spigel & Harrison, 2018; Senyo et al., 2021; Molla & Biru, 2023; Wurth et al., 2023).

One plausible mechanism behind the negative supply-side coefficient is incumbent capture. Firms that already possess the organisational capabilities, human capital, market access, and financial resources needed to exploit digital channels are best positioned to benefit from improved connectivity and infrastructure. Prospective entrants, by contrast, may remain constrained by weak adoption capabilities, limited digital financial literacy, low trust in digital services, and incomplete integration with formal institutions. Under such conditions, infrastructure expansion may widen capability gaps rather than lower entry barriers, generating a net drag on formal entry that aggregate infrastructure measures would not reveal.

Notwithstanding the limits of country-level data, which cannot directly verify incumbent capture or observe the within-country allocation of digital infrastructure gains, the demand–supply asymmetry is robust across specifications and consistent with firm-level evidence that mobile money and digital financial tools generate stronger productivity and financing effects when combined with complementary financial relationships and organisational capabilities (Dalton et al., 2023; Gosavi, 2018; Konte & Tetteh, 2023; Tetteh et al., 2025). FinTech ecosystems operate as adoption–capability systems rather than infrastructure systems, with direct implications for the design and evaluation of digital entrepreneurship policy.

5.2 Credit-Market Segmentation and Monetary Substitution

Private credit depth does not moderate the FinTech–entry relationship ($\gamma_1 = 0.001$, $p = 0.45$). Broad monetary depth does, and negatively so ($\gamma_2 = -0.003$, $p = 0.004$). The two null and non-null results reflect distinct features of the Sub-Saharan African financial structure.

Aggregate private credit largely reflects lending to firms already integrated into the formal banking system. Prospective entrants typically rely on internal finance, family resources, informal credit, microfinance, or trade credit, channels orthogonal to aggregate credit depth. African banking sectors are often liquid and well-capitalised, yet lend comparatively little to the private sector, and households and firms remain less likely to use formal financial services than their counterparts in other developing regions (Beck & Cull, 2013; Beck et al., 2019; De Cleene & Wood, 2004; Van Empel, 2010). FinTech adoption expands payment capability, savings behaviour, transaction records, and basic financial access among underbanked users, a different margin entirely. Private credit depth and FinTech development, therefore, operate through different channels, and the null interaction is what the segmentation hypothesis predicts.

Broad money captures a wider set of monetary services: deposit-taking, payment intermediation, savings instruments, and liquidity management provided by the established banking system. Where these services are already widely available, FinTech may duplicate rather than extend existing functions. The marginal entrepreneurial value of FinTech development is accordingly lower in deeper conventional monetary infrastructure, consistent with evidence that new firm creation is more closely linked to formal financial conditions in deeper financial markets (Klapper & Love, 2010; Klapper et al., 2014).

The marginal-effect profile confirms this. The FinTech entry association remains positive across 95 per cent of the broad-money distribution but attenuates in the upper tail. The implied zero-crossing falls at 96.4 per cent of GDP, within the empirical support of broad money but near its upper boundary. The result indicates localised attenuation, not a general reversal: FinTech ecosystem development continues to promote formal entry across most of the sample, but the marginal return diminishes where conventional financial systems already provide equivalent payment and liquidity-management services.

5.3 Methodological Implication: Interpreting Moderation Effects

A negative interaction coefficient does not uniquely identify whether the underlying effect attenuates with the moderator or reverses sign within the observed sample. These cases have distinct theoretical and policy interpretations, yet they are rarely distinguished in applied panel analyses (Assaf et al., 2020; Baranger et al., 2023; Becker et al., 2018).

This distinction can be evaluated by locating the zero of the implied marginal-effect function within the empirical support for the moderator. When the zero lies outside the observed range, the interaction reflects attenuation without reversal. When it lies within the range, the marginal effect changes sign for a subset of observations, implying heterogeneity across the moderator distribution. Boundary cases require assessing whether the sign change applies to a quantitatively relevant share of the sample.

In the present setting, the zero-crossing occurs at a broad money ratio of 96.4 per cent of GDP, which falls within the empirical support but near the upper tail of the distribution. The estimated association between FinTech ecosystem development and formal firm entry remains positive for roughly 95 per cent of country–year observations and weakens only at the highest levels of monetary depth. The interaction is therefore consistent with partial substitution characterised by localised attenuation, rather than a pervasive negative effect of FinTech entry in deeper financial systems.

5.4 Policy Implications

The findings point to three policy implications for digital entrepreneurship and financial-sector development in Sub-Saharan Africa.

FinTech policy should prioritise adoption capability over infrastructure expansion alone. Formal entrepreneurial entry is more closely associated with the actual use of digital financial services than with the availability of infrastructure. Investments in mobile connectivity, broadband, and electricity may therefore have limited entrepreneurial returns unless accompanied by interventions that increase trust, usability, affordability, and effective use among prospective entrepreneurs. Digital financial tools generate stronger productivity and financing effects when they reduce transaction frictions, support trade credit, and complement existing financial

relationships (Aron, 2018; Gosavi, 2018; Beck et al., 2018; Konte & Tetteh, 2023; Dalton et al., 2023; Tetteh et al., 2025).

Demand-side interventions should target the practical barriers that prevent entrepreneurs from using digital finance for business formation and operations: digital financial literacy, merchant payment acceptance, agent network reliability, interoperability, transparent pricing, consumer protection, and simplified onboarding for micro and small enterprises. Formal entry requires not just access to technology but the ability to transact, save, receive payments, build financial records, and interact with formal institutions.

Policy priorities should also reflect the macro-financial context. In economies with shallow monetary systems, FinTech can fill gaps in payments, savings, and liquidity management. In economies where conventional financial institutions already provide these services, the marginal entrepreneurial return to additional FinTech investment is smaller. For the latter, policy should focus less on expanding FinTech infrastructure and more on competition, interoperability, and inclusion of underserved groups (Klapper & Love, 2010; Klapper et al., 2014; Munemo, 2018).

The negative supply-side coefficient reinforces these implications. Infrastructure investments are necessary but not sufficient. Without adoption-oriented policies that ensure new and smaller firms can use digital channels effectively, infrastructure improvements risk disproportionately benefiting incumbents already positioned to exploit them.

5.5 Limitations and Future Research

Five limitations define the scope of the findings.

The demand sub-index is constructed from Global Findex indicators observed at discrete survey waves, with annual values obtained through period-score replication. The anchor-year robustness check shows that the main association holds when estimation is restricted to years in which Findex indicators are directly observed, reducing concerns about within-period artefacts. Higher-frequency mobile money transaction data or regulatory records could be used to examine the timing of FinTech effects with greater precision.

The cross-country panel design cannot identify firm-level heterogeneity. The estimates represent average country-level associations and cannot distinguish effects by firm size, sector, ownership structure, gender of ownership, or financing strategy. Existing firm-level evidence shows that the effects of mobile money and digital finance vary by firm characteristics and complementary financial relationships (Gosavi, 2018; Konte & Tetteh, 2023; Beck et al., 2018; Tetteh et al., 2025). Linking national FinTech ecosystem measures to firm-level datasets such as the World Bank Enterprise Surveys could identify which entrepreneurs benefit most.

The analysis does not model joint dynamics among FinTech ecosystem development, monetary depth, private credit, and entrepreneurial entry. These variables may evolve together and involve feedback effects. Panel vector autoregression or structural dynamic models could examine how shocks to one part of the financial ecosystem propagate through the others.

The country-level design masks within-country heterogeneity. Digital infrastructure, mobile money agent density, and formal business registration are often concentrated in urban areas. Subnational data would allow future studies to examine whether FinTech ecosystem effects differ across regions, cities, and rural economies.

The study does not assess the distributional consequences of FinTech-led entrepreneurial development. Aggregate increases in formal entry may coexist with unequal access, platform dependency, or uneven benefits across social groups. Platform-based financial inclusion can reproduce inequality and new forms of extraction even as aggregate adoption indicators improve (Gabor & Brooks, 2017; Langley & Leyshon, 2022). Future research should connect macro-level ecosystem development to micro-level outcomes such as income mobility, gendered access to entrepreneurship, firm survival, and distributional inclusion.

5.6 Conclusion

This paper documents a positive association between FinTech ecosystem development and formal entrepreneurial entry across 46 Sub-Saharan African economies over the period 2014–2022. The relationship is driven by demand-side adoption rather than supply-side infrastructure. Conditional on adoption, greater infrastructure provision is negatively associated with formal entry, consistent with incumbent capture of digital channels in environments where population-level behavioural adoption lags behind technological deployment.

The macro-financial environment shapes this relationship. Private credit depth does not moderate the FinTech–entry association, consistent with segmented credit markets in which formal lending disproportionately serves incumbents rather than prospective entrants (Beck & Cull, 2013; Beck et al., 2019). By contrast, broader monetary depth attenuates the association, consistent with partial substitution: where conventional financial systems already provide payment, savings, and liquidity management services, the marginal entrepreneurial returns to FinTech development are lower.

Identification diagnostics support a directional interpretation from FinTech ecosystem development to formal entry, although the observational nature of the data precludes definitive causal inference. The central policy implication follows from the demand–supply asymmetry identified in the results: entrepreneurial gains from FinTech development depend on adoption capability, usability, and integration into the routine financial practices of prospective entrepreneurs, rather than on infrastructure expansion alone.

Declarations

Ethical Approval and Consent to Participate

Not applicable. This study uses publicly available secondary data and does not involve human participants, animal subjects, or identifiable personal information. No ethical approval or consent to participate was required.

Consent for Publication

Not applicable. This study does not contain data from any individual person.

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References

Ahmad, A. H., Green, C., & Jiang, F. (2020). Mobile money, financial inclusion and development: A review with reference to African experience. *Journal of Economic Surveys*, 34(4), 753–792.

- Alaassar, A., Mention, A., & Aas, T. (2021). Ecosystem dynamics: exploring the interplay within fintech entrepreneurial ecosystems. *Small Business Economics*, 58, 2157–2182. <https://doi.org/10.1007/s11187-021-00505-5>
- Arcand, J., Berkes, E., & Panizza, U. (2015). Too much finance? *Journal of economic growth*, 20, 105–148. <https://doi.org/10.1007/s10887-015-9115-2>
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29–51.
- Aron, J. (2018). Mobile Money and the Economy: A Review of the Evidence. *The World Bank Research Observer*. <https://doi.org/10.1093/wbro/lky001>
- Arslan, A., Buchanan, B., Kamara, S., & Nabulsi, N. A. (2021). Fintech, base of the pyramid entrepreneurs and social value creation. *Journal of Small Business and Enterprise Development*. <https://doi.org/10.1108/jsbed-10-2020-0370>
- Assaf, A., Tsionas, M., & Andrikopoulos, A. (2020). Testing moderation effects using non-parametric regressions. *International Journal of Hospitality Management*. <https://doi.org/10.1016/j.ijhm.2019.102441>
- Assenova, V. (2021). Regulatory Reforms and Entrepreneurs' Choices of Firm Structure: Evidence from Sub-Saharan Africa. *Academy of Management Proceedings*. <https://doi.org/10.5465/ambpp.2021.10268abstract>
- Baranger, D., Finsaas, M., Goldstein, B., Vize, C., Lynam, D., & Olino, T. (2023). Tutorial: Power Analyses for Interaction Effects in Cross-Sectional Regressions. *Advances in Methods and Practices in Psychological Science*, 6. <https://doi.org/10.1177/25152459231187531>
- Beck, T., & Cull, R. (2013). *Banking in Africa* (Policy Research Working Paper Issue).
- Beck, T., Cull, R., & Valenzuela, P. (2019). Banking in Africa. *The Oxford Handbook of Banking*. <https://doi.org/10.1093/oxfordhb/9780198824633.013.34>
- Beck, T., Pamuk, H., Ramrattan, R., & Uras, B. R. (2018). Payment instruments, finance and development. *Journal of Development Economics*, 133, 162–186. <https://doi.org/https://doi.org/10.1016/j.jdeveco.2018.01.005>
- Becker, J.-M., Ringle, C., & Sarstedt, M. (2018). ESTIMATING MODERATING EFFECTS IN PLS-SEM AND PLSc-SEM: INTERACTION TERM GENERATION*DATA TREATMENT. *Journal of Applied Structural Equation Modeling*. [https://doi.org/10.47263/jasem.2\(2\)01](https://doi.org/10.47263/jasem.2(2)01)

- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115–143.
- Chinoda, T., & Kapingura, F. (2023). Digital financial inclusion and economic growth in Sub-Saharan Africa: the role of institutions and governance. *African Journal of Economic and Management Studies*.
<https://doi.org/10.1108/ajems-09-2022-0372>
- Dalton, P., Pamuk, H., Ramrattan, R., Uras, B., & Soest, D. (2023). Electronic Payment Technology and Business Finance: A Randomized, Controlled Trial with Mobile Money. *Management Science*, 70, 2590–2625.
<https://doi.org/10.1287/mnsc.2023.4821>
- Dalton, P., Pamuk, H., Soest, D., Ramrattan, R., & Uras, B. (2017). Technology Adoption by Small and Medium Businesses : Experimental Evidence from Mobile Money in Kenya.
- Dalton, P., Pamuk, H., Soest, D., Ramrattan, R., & Uras, B. (2018). Payment Technology Adoption by SMEs : Experimental Evidence from Kenya's Mobile Money.
- De Cleene, S., & Wood, C. (2004). Sustainability banking in Africa. 1–84.
- Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80(4), 549–560.
- Etudaiye-Muhtar, F. O., Johan, S., Lawal, R., & Sakariyahu, R. (2023). Fintech, human development and energy poverty in sub-Saharan Africa. *Journal of International Financial Markets, Institutions and Money*.
<https://doi.org/10.1016/j.intfin.2023.101931>
- Fox, J., & Monette, G. (1992). Generalized collinearity diagnostics. *Journal of the American Statistical Association*, 87(417), 178–183.
- Frimanslund, T. (2022). Financial Entrepreneurial Ecosystems: An Analysis of Urban and Rural Regions of Norway. *International Journal of Global Business and Competitiveness*, 17, 24–39. <https://doi.org/10.1007/s42943-022-00050-2>
- Gabor, D., & Brooks, S. (2017). The digital revolution in financial inclusion: international development in the fintech era. *New Political Economy*, 22, 423–436. <https://doi.org/10.1080/13563467.2017.1259298>
- Gosavi, A. (2018). Can Mobile Money Help Firms Mitigate the Problem of Access to Finance in Eastern sub-Saharan Africa? *Journal of African Business*, 19, 343–360. <https://doi.org/10.1080/15228916.2017.1396791>

- Ha, D., Le, P., & Nguyen, D. K. (2025). Financial inclusion and fintech: a state-of-the-art systematic literature review. *Financial Innovation*, 11(1), 69.
- Haddad, C., & Hornuf, L. (2018). The emergence of the global fintech market: economic and technological determinants. *Small Business Economics*, 53(1), 81–105. <https://doi.org/10.1007/s11187-018-9991-x>
- Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: journal of the Econometric Society*, 1251–1271.
- Kamara, A. K., & Yu, B. (2024). The impact of FinTech adoption on traditional financial inclusion in Sub-Saharan Africa. *Risks*, 12(7), 115.
- Kedir, A., & Kouame, E. (2022). FinTech and women's entrepreneurship in Africa: the case of Burkina Faso and Cameroon. *Journal of Cultural Economy*, 15(4), 452–467. <https://doi.org/10.1080/17530350.2022.2041463>
- Klapper, L., Laeven, L., & Rajan, R. (2006). Entry regulation as a barrier to entrepreneurship. *Journal of Financial Economics*, 82, 591–629. <https://doi.org/10.1016/j.jfineco.2005.09.006>
- Klapper, L., & Love, I. (2010). The Impact of the Financial Crisis on New Firm Registration. *Economics Letters*, 113, 1–4. <https://doi.org/10.1596/1813-9450-5444>
- Klapper, L., Love, I., & Randall, D. (2014). New firm registration and the business cycle. *International Entrepreneurship and Management Journal*, 11, 287–306. <https://doi.org/10.1007/s11365-014-0345-0>
- Klapper, L., Singer, D., Starita, L., & Norris, A. (2025). *The Global Findex Database 2025: Connectivity and Financial Inclusion in the Digital Economy*. (The Global Findex Database 2025: Connectivity and Financial Inclusion in the Digital Economy., Issue. <https://openknowledge.worldbank.org/server/api/core/bitstreams/795d71b1-9df7-4c04-a11d-75d1d8bbcf2f/content>
- Konte, M., & Tetteh, G. K. (2023). Mobile money, traditional financial services and firm productivity in Africa. *Small Business Economics*, 60(2), 745–769.
- Koroleva, E. (2022). FinTech Entrepreneurial Ecosystems: Exploring the Interplay between Input and Output. *International Journal of Financial Studies*. <https://doi.org/10.3390/ijfs10040092>
- Kouladoum, J., Wirajing, M. A. K., & Nchofoung, T. (2022). Digital technologies and financial inclusion in Sub-Saharan Africa. *Telecommunications Policy*. <https://doi.org/10.1016/j.telpol.2022.102387>

- Langley, P., & Leyshon, A. (2022). Neo-colonial credit: FinTech platforms in Africa. *Journal of Cultural Economy*, 15(4), 401–415. <https://doi.org/10.1080/17530350.2022.2028652>
- Molla, A., & Biru, A. (2023). The evolution of the Fintech entrepreneurial ecosystem in Africa: An exploratory study and model for future development. *Technological Forecasting and Social Change*, 186. <https://doi.org/10.1016/j.techfore.2022.122123>
- Munemo, J. (2018). Entrepreneurial Success in Africa: How Relevant Are Foreign Direct Investment and Financial Development? *African Development Review*. <https://doi.org/10.1111/1467-8268.12345>
- Noah, A., & Olalekan, D. O. (2025). Does Financial Development Drive Entrepreneurship in Africa? A Panel Data Analysis. *Managing Global Transitions*. <https://doi.org/10.26493/1854-6935.23.49-78>
- Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics*, 60(1), 13–50.
- Sanga, B., & Aziakpono, M. (2022). The impact of technological innovations on financial deepening: Implications for SME financing in Africa. *African Development Review*. <https://doi.org/10.1111/1467-8268.12668>
- Sanga, B., & Aziakpono, M. (2024). FinTech developments and their heterogeneous effect on digital finance for SMEs and entrepreneurship: evidence from 47 African countries. *Journal of Entrepreneurship in Emerging Economies*, 17(7), 127–155. <https://doi.org/10.1108/jeeee-09-2023-0379>
- Senyo, P. K., Karanasios, S., Gozman, D., & Baba, M. (2021). FinTech ecosystem practices shaping financial inclusion: the case of mobile money in Ghana. *European Journal of Information Systems*, 31(1), 112–127. <https://doi.org/10.1080/0960085x.2021.1978342>
- Shi, X., & Shi, Y. (2021). Unpacking the process of resource allocation within an entrepreneurial ecosystem. *Research Policy*. <https://doi.org/10.1016/j.respol.2021.104378>
- Spigel, B. (2022). Examining the cohesiveness and nestedness entrepreneurial ecosystems: evidence from British FinTechs. *Small Business Economics*, 59(4), 1381–1399. <https://doi.org/10.1007/s11187-021-00589-z>
- Spigel, B., & Harrison, R. (2018). Towards a process theory of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal*, 12, 151–168. <https://doi.org/10.1002/sej.1268>
- Tetteh, G. K., Goedhuys, M., Konte, M., & Mohnen, P. (2025). Mobile Money Use and Entrepreneurs' Access to Trade Credit in the Informal Sector. *Review of Development Economics*. <https://doi.org/10.1111/rode.13223>
- Van Empel, G. (2010). Rural banking in Africa.

- Voptia, E. B. K., & Stukalina, Y. (2025). Financial Inclusion in Sub-Saharan Africa: The Case of Mobile Money. *Ekonomika*. <https://doi.org/10.15388/ekon.2024.103.4.5>
- World Bank. (2024). *World Bank Indicators*. World Bank Group. <https://databank.worldbank.org/source/world-development-indicators>
- Wu, D.-M. (1973). Alternative tests of independence between stochastic regressors and disturbances. *Econometrica: journal of the Econometric Society*, 733–750.
- Wurth, B., Stam, E., & Spigel, B. (2023). Entrepreneurial Ecosystem Mechanisms. *Foundations and Trends® in Entrepreneurship*. <https://doi.org/10.1561/03000000089>
- Yao, B., Shanoyan, A., Schwab, B., & Amanor-Boadu, V. (2022). Mobile money, transaction costs, and market participation: evidence from Côte d'Ivoire and Tanzania. *Food Policy*. <https://doi.org/10.1016/j.foodpol.2022.102370>

Appendix

A. Sample and Variable Construction

A.1 Estimation Sample

Table A1 reports the 46 Sub-Saharan African economies included in the analysis.

Table A1. Sample Economies

ISO3	Country	ISO3	Country	ISO3	Country
AGO	Angola	GIN	Guinea	RWA	Rwanda
BDI	Burundi	GMB	The Gambia	SDN	Sudan
BEN	Benin	GNB	Guinea-Bissau	SEN	Senegal
BFA	Burkina Faso	GNQ	Equatorial Guinea	SOM	Somalia
BWA	Botswana	KEN	Kenya	SSD	South Sudan

ISO3	Country	ISO3	Country	ISO3	Country
CAF	Central African Republic	LBR	Liberia	STP	São Tomé and Príncipe
CIV	Côte d'Ivoire	LSO	Lesotho	SWZ	Eswatini
CMR	Cameroon	MDG	Madagascar	SYC	Seychelles
COD	Democratic Republic of the Congo	MLI	Mali	TCD	Chad
COG	Republic of the Congo	MOZ	Mozambique	TGO	Togo
COM	Comoros	MRT	Mauritania	TZA	Tanzania
CPV	Cabo Verde	MUS	Mauritius	UGA	Uganda
ERI	Eritrea	MWI	Malawi	ZAF	South Africa
ETH	Ethiopia	NAM	Namibia	ZMB	Zambia
GAB	Gabon	NER	Niger		
GHA	Ghana	NGA	Nigeria		

Note: Countries are sorted alphabetically by ISO3 code. The initial country-year frame covers 46 economies observed from 2014 to 2022. Model-specific observation counts vary according to data availability and complete-case requirements.

A.2 Variable Definitions and Sources

Table A2 defines the variables used in the analysis.

Table A2. Variable Definitions and Sources

Role	Variable	Definition	Source	Code
Dependent variable	$\ln(1 + NBD)$	Log of one plus new business density, measured as newly registered corporations per 1,000 working-age adults	WDI / World Bank Entrepreneurship Database	IC.BUS.NDNS.ZS
Alternative dependent variable	$\ln(1 + nreg)$	Log of one plus the number of newly registered corporations	WDI / World Bank Entrepreneurship Database	IC.BUS.NREG
Principal regressor	<i>FNT_ECO</i>	Composite FinTech ecosystem index; PC1 of the standardised demand and supply sub-indices	Constructed	—
Sub-index	<i>Demand_z</i>	Standardised Stage-1 PCA score based on wave-specific Finindex behavioural indicators	Constructed Finindex	from —
Sub-index	<i>Supply_z</i>	Standardised Stage-1 PCA score based on four WDI infrastructure indicators	Constructed WDI	from —
Moderator	<i>CRD</i>	Private credit to GDP, mean-centred on the estimation sample	WDI	FS.AST.PRVT.GD.ZS
Moderator	<i>BM</i>	Broad money to GDP, mean-centred on the estimation sample	WDI	FM.LBL.BMNY.GD.ZS

Role	Variable	Definition	Source	Code
Control	Log GDP per capita	Natural logarithm of GDP per capita, constant 2015 US dollars	WDI	NY.GDP.PCAP.KD
Control	Inflation	Consumer price inflation, annual percentage	WDI	FP.CPI.TOTL.ZG
Control	Trade openness	Exports plus imports of goods and services as a percentage of GDP		NE.TRD.GNFS.ZS

Note: WDI = World Development Indicators (World Bank, 2024). Findex = Global Findex Database (Klapper et al., 2025). The demand-side PCA uses wave-specific Findex indicators because indicator availability differs across survey waves.

A.3 Findex Period-Score Replication

Global Findex indicators are observed at discrete survey waves — 2011, 2014, 2017, and 2021 — rather than annually. To obtain annual demand-side observations for the estimation period of 2014–2022, wave-specific PCA scores are assigned to three-year windows: the 2014 score to 2014–2016, the 2017 score to 2017–2019, and the 2021 score to 2020–2022. This procedure preserves the discrete-wave structure of the underlying data and avoids imposing artificial annual variation through linear interpolation, which would introduce within-window trends that are not present in the source data.

The anchor-year robustness check in Table 8 directly addresses the sensitivity of the results to this construction. Restricting the estimation sample to the three Findex anchor years — 2014, 2017, and 2021 — yields a positive and statistically significant coefficient on FNT_ECO of $\beta = 0.137$ ($p < 0.001$), confirming that the main association is not an artefact of the period-replication procedure.

A.4 Country Exclusions

Two economies are excluded from the estimation sample due to data comparability.

Zimbabwe is excluded because recurrent currency instability and hyperinflationary episodes, including the 2007–2009 hyperinflation, the 2019 reintroduction of the Zimbabwe dollar, and subsequent inflationary episodes through 2022, produce CPI inflation readings and GDP per capita revisions that are not comparable with other sample economies. These episodes would distort the within-country variation on which the fixed-effects estimator relies, rather than representing genuine FinTech or entrepreneurship dynamics.

Sierra Leone is excluded because of irregularities in the new business density series during the study period. Inspection of the IC.BUS.NDNS.ZS series reveals reporting anomalies that are inconsistent with the country's documented entrepreneurial entry pattern in alternative sources. Rather than attempting manual correction of potentially contaminated observations, the conservative approach of full exclusion is adopted.

B. Detailed PCA Construction

B.1 Stage 1 Supply Sub-Index

Table B1 reports the variance decomposition for the supply-side PCA. The first principal component explains 72.7 per cent of the variance across the four standardised infrastructure indicators and is retained as the supply-side sub-index.

Table B1. Stage 1 Supply Sub-Index: PCA Variance Decomposition

Component	Eigenvalue	Variance share	Cumulative share
PC1	2.907	72.7%	72.7%
PC2	0.581	14.5%	87.2%
PC3	0.303	7.6%	94.8%
PC4	0.209	5.2%	100.0%

Note: PCA estimated on the four standardised supply-side indicators: internet use, electricity access, mobile cellular subscriptions, and fixed broadband subscriptions. The sign of PC1 is anchored on internet use.

B.2 Stage 1 Demand Sub-Index

Table B2 reports demand-side PCA loadings across Findex waves. Indicator availability varies by wave. PC1 explains between 70.7 and 96.4 per cent of the variance across waves.

Table B2. Stage 1 Demand Sub-Index: PCA Loadings Across Findex Waves

Indicator	2011–2013	2014–2016	2017–2019	2020–2022
Financial institution account	0.583	0.371	0.327	0.253
Mobile money account	—	0.255	0.330	0.268
Account ownership, total	0.583	0.409	0.386	0.338
Borrowed using mobile money	—	—	—	0.239
Made a digital payment	—	0.401	0.379	0.352
Made or received a digital payment	—	0.411	0.386	0.347
Received a digital payment	—	0.409	0.385	0.335
Saved via mobile money	0.566	0.364	0.277	0.328
Saved using mobile money	—	—	—	0.221
Mobile/internet bill payment	—	—	0.344	0.294
Online purchase using a mobile phone/internet	—	—	—	0.305
PC1 variance share	96.4%	82.5%	81.5%	70.7%

Note: Each column reports PC1 loadings for the corresponding Findex-based period. Em-dashes indicate indicators that were not included due to insufficient wave-specific availability. The sign of PC1 is anchored on mobile money account ownership, where available.

B.3 Stage 2 Composite Ecosystem Index

Table B3 reports the variance decomposition for the second-stage PCA. PC1 explains 79.1 per cent of the variance in the standardised demand–supply input space.

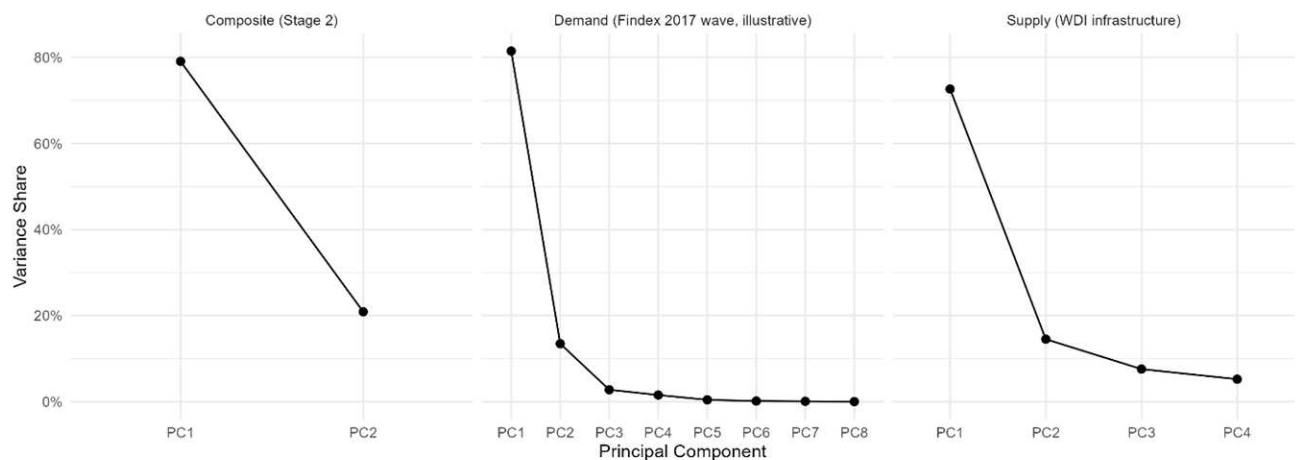
Table B3. Stage 2 Composite Ecosystem Index: PCA Variance Decomposition

Component	Eigenvalue	Variance share	Cumulative share
PC1	1.405	79.1%	79.1%
PC2	0.371	20.9%	100.0%

Note: PCA estimated on the standardised demand and supply sub-indices. The sign of PC1 is anchored on the demand-side sub-index.

B.4 Scree Plots

Figure A1. Scree Plots for the PCA-Based Index Construction



Note: Panel A reports the scree plot for the supply-side PCA. Panel B reports the illustrative 2017–2019 demand-side PCA. Panel C reports the second-stage composite PCA based on the standardised demand and supply sub-indices.

C. Detailed Marginal Effects

Table C1 reports the marginal effect of *FNT_ECO* across selected percentiles of the broad-money distribution.

Table C1. Marginal Effect of *FNT_ECO* Across the Broad-Money Distribution

Percentile	BM, % of GDP	Marginal effect	Std. error	95% CI
10th	18.2	0.2426	0.0464	[0.1517, 0.3335]
25th	22.4	0.2298	0.0426	[0.1462, 0.3134]
50th	28.4	0.2111	0.0375	[0.1377, 0.2845]
75th	42.2	0.1682	0.0275	[0.1143, 0.2222]
90th	65.4	0.0962	0.0251	[0.0469, 0.1454]
95th	89.7	0.0209	0.0423	[−0.0620, 0.1038]

Note: Marginal effects are computed from the joint moderation specification in column (4) of Table 5, holding private credit at its sample mean. The marginal effect is calculated as $\beta_1 + \gamma_2 BM$. Standard errors are computed from the joint covariance matrix. The implied zero-crossing is $BM^* = 96.4$ per cent of GDP, above the 95th percentile but within the observed range.

D. Estimators Considered but Not Adopted

D.1 Common Correlated Effects Pooled Estimator

The Pesaran (2006) Common Correlated Effects pooled estimator was considered as a robustness check for unobserved common factors. However, the Pesaran (2021) cross-sectional dependence test fails to reject the null

of cross-sectional independence in the baseline residuals ($CD = 0.77$, $p = 0.44$), thereby reducing the empirical motivation for this estimator in the present setting. Consistent with this diagnostic, the CCE-pooled estimate is imprecise: the coefficient on FNT_ECO is -0.625 with a standard error of 0.816 , yielding a confidence interval that encompasses both the fixed-effects baseline of 0.182 and economically large negative values. The estimate is therefore not statistically distinguishable from the baseline result and is not reported in the main robustness table.

D.2 Nigeria-Exclusion Specification

A Nigeria-exclusion specification was considered alongside the South Africa exclusion in Table 8. The coefficient on FNT_ECO is indistinguishable from the baseline estimate at the reported precision, because Nigerian observations do not enter the complete-case estimation sample owing to missingness in the demand-side Findex indicators. Excluding Nigeria, therefore, does not change the effective estimation sample, and reporting an identical column would convey no additional information. The specification is documented here for transparency rather than reported as a separate robustness column.