Finance Research Letters 84 (2025) 107776

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Disaggregating digital financial inclusion in Africa: Explaining within- and between-country variance

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ARTICLE INFO

Keywords:
Digital financial inclusion
Fintech
Digital payments
Paytech
Africa

ABSTRACT

This study examines the extent to which individual- and country-level characteristics account for variations in the use of digital payments across 36 African countries. Using a two-level random intercept multilevel probit model, we analyse cross-sectional data to estimate the probability of digital financial inclusion while accounting for the hierarchical structure of individuals nested within countries. The analysis quantifies the proportion of variance in digital payment usage that is attributable to country-level versus individual-level factors, using intraclass correlation coefficients (ICCs). The results reveal that most of the explained variance (75 %) stems from individual characteristics like age, education, gender, income, employment, and internet access. However, country-level factors;particularly national education levels and employment levels, also play a meaningful role. These findings highlight the importance of both micro- and macro-level determinants in shaping digital financial behaviours and demonstrate the need for context-sensitive policies to promote inclusive digital finance.

1. Introduction

Digital financial inclusion has emerged as a powerful driver of inclusive development in sub-Saharan Africa, where many individuals remain excluded from traditional financial systems due to geographic remoteness, poverty, and underdeveloped banking infrastructure (Kouladoum et al., 2022). The rapid proliferation of mobile money platforms, fintech innovations, and digital payment systems has enabled millions across the region to access financial services, even in areas previously considered too costly or remote to serve (Basnayake et al., 2024). This digital transformation has led to a growing body of research seeking to identify the determinants of digital financial inclusion. Prior studies have shown that both individual-level characteristics—such as income, education, gender, and age (e.g., Nyakurukwa et al., 2025)—and macro-level factors—such as internet penetration, regulatory quality, inflation, and GDP per capita (e.g., Daud and Ahmad, 2023)—can significantly shape access to and use of digital financial services.

However, while several studies have incorporated both micro- and macro-level variables, they typically rely on estimation strategies, such as pooled regression or fixed effects models, that do not fully account for the nested structure of the data. Pooled regression models treat all observations as independent, failing to adjust for the fact that individuals within the same country are likely to share contextual influences such as regulatory conditions, technological infrastructure, or cultural norms. This can result in biased standard errors and overconfident inferences (Moulton, 1990). Similarly, while fixed effects models can control for unobserved heterogeneity

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https://doi.org/10.1016/j.frl.2025.107776
Received 3 May 2025; Received in revised form 30 May 2025; Accepted 14 June 2025
Available online 15 June 2025

across countries, they do so by removing all between-country variation, which makes it impossible to assess how much of the variation in digital financial inclusion is explained at the country level (Möhring, 2021).

This study addresses these limitations by adopting a multilevel modelling framework that explicitly recognises the hierarchical nature of digital financial inclusion data. Individuals are not isolated units but are embedded within national contexts that differ significantly in terms of economic development, institutional quality, and digital readiness (Oshchepkov and Shirokanova, 2022). By modelling individuals as nested within countries, we decompose the total variance in digital financial inclusion into within-country and between-country components. This decomposition is captured by the intra-class correlation coefficient (ICC), which quantifies the proportion of total variance attributable to differences between countries (Devine et al., 2024).

The study finds that individual characteristics—especially age, education, gender, income, employment, mobile phone ownership and internet access—are the primary drivers of digital payment usage, explaining 75 % of the variance. Country-level factors, notably education and employment levels contribute 25 % of the variance. The ICC declines across increasingly inclusive models—from the null model to those including individual- and country-level predictors—indicating that much of the between-country variance is explained by the added covariates. However, some residual ICC remains, showing that unobserved country-level influences still play a role.

The key contribution of this study lies not in merely combining individual and macro-level variables—a methodological approach that has been used before—but in formally quantifying the variance explained at each level. By calculating the ICC, the study provides a clear estimate of the relative importance of national context versus individual attributes in shaping digital financial inclusion outcomes. This approach enables a more precise identification of whether policy attention should be directed toward structural reforms at the national level or targeted interventions at the individual level.

We proceed as follows: Section 2 outlines the data and methods used in the study, Section 3 presents the results, and Section 4 concludes.

2. Data and methods

2.1. Data

The study utilises individual-level cross-sectional data from the 2021 Global Findex Database, a globally recognised source offering detailed insights into how adults manage financial activities. The analysis focuses on non-institutionalised civilians aged 15 and older. Country-specific indicators were supplemented with World Development Indicators data. The dataset consists of 36,062 individuals from 36 sub-Saharan African countries. Table 1 summarises the individual- and country-level variables incorporated in the analysis.

2.2. Methods

The study employs a two-level random intercept multilevel probit model to estimate the likelihood of digital payment use, with individuals nested within countries. This approach accounts for the clustering of individuals within countries and corrects the underestimation of standard errors, especially for country-level predictors (Devine et al., 2024). Four models are estimated sequentially.

Table 1
List of variables.

VARIABLE	DEFINITION	SOURCE
	Main dependent variable	
Any digital payment	Equals 1 if an individual received or made any digital payment and 0 otherwise	2021 Global Findex Database
	Alternative dependent variables	
Mobile in-store purchases	Equals 1 if an individual used a mobile phone to pay for a purchase in-store and 0 otherwise	2021 Global Findex Database
Internet bill payments	Equals 1 if an individual made bill payments online using the internet and 0 otherwise	2021 Global Findex Database
	Individual-level covariates	
Age	The natural logarithm of respondent age	2021 Global Findex Database
Age squared	Square of Age	Author calculation
Secondary	Equals 1 if the individual has a minimum of secondary education and 0 otherwise	2021 Global Findex Database
Female	Equals 1 if the individual is female and 0 otherwise	2021 Global Findex Database
Employed	Equals 1 if an individual is employed and 0 otherwise	2021 Global Findex Database
Mobile owner	Equals 1 if an individual owns a mobile phone and 0 otherwise	2021 Global Findex Database
Internet	Equals 1 if an individual has access to the internet and 0 otherwise	2021 Global Findex Database
Income	Findex uses poverty/consumption-based quintiles to compare financial inclusion gaps.	2021 Global Findex Database
	Country-level covariates	
Employed Prop	Proportion of population employed	World Bank
Secondary prop	The proportion of the population with a minimum of secondary education	World Bank
Mobile prop	The proportion of the population with a mobile phone	World Bank
Urban prop	The proportion of the population staying in urban areas	World Bank
Inflation	Annual rate of inflation	World Bank
Economic Growth	Annual economic growth rate as measured by GDP	World Bank
Gov effectiveness	A continuous variable that measures the government's effectiveness	Worldwide Governance Indicators
Reg quality	A continuous variable that measures regulatory quality	Worldwide Governance Indicators

The null model includes only a random intercept, providing a baseline measure of variation in digital payment use across countries. The second and third models include only individual- and country-level variables, respectively. The baseline model is specified as:

$$\Phi^{-1}\left(P_{ij}\right) = \beta_0 + X_{ij}\beta + Z_j\gamma + u_{0j} \tag{1}$$

where $\Phi^{-1}(P_{ij})$ is the probit link of the probability that individual i in country $j$uses digital payments, X_{ij} and Z_j are vectors of individual and country-level predictors, respectively, and $u_{0j}\sim N(0,\sigma_u^2)$ is the country-specific random intercept. The ICC is used to quantify the proportion of total variance in digital financial inclusion between countries. In multilevel probit models, the ICC is approximated using the latent response formulation, calculated as:

$$ICC = \frac{\sigma_u^2}{\sigma_u^2 + 3.29} \tag{2}$$

Table 2
Results from the multilevel models.

	(1)	(2)	(3)	(4)
Age		4.8663***		4.8632***
		(0.5249)		(0.5249)
Age squared		−0.6192***		−0.6188***
		(0.0750)		(0.0750)
Female		−0.1213***		−0.1209***
		(0.0271)		(0.0271)
Secondary		0.7154***		0.7123***
		(0.0304)		(0.0304)
Income				
Quintile 2		0.2401***		0.2402***
		(0.0456)		(0.0456)
Quintile 3		0.4331***		0.4333***
		(0.0445)		(0.0445)
Quintile 4		0.5221***		0.5226***
		(0.0436)		(0.0436)
Quintile 5		0.8381***		0.8391***
		(0.0429)		(0.0429)
Employed		0.6722***		0.6716***
		(0.0308)		(0.0308)
Internet		1.0370***		1.2041***
		(0.0313)		(0.0365)
Mobile owner		1.2050***		1.2041***
		(0.0365)		(0.0365)
Inflation			0.0026	0.0014
			(0.0101)	(0.0111)
Employed Prop			2.2793**	2.0867*
			(1.1040)	(1.2183)
Secondary prop			3.5865***	2.2631***
			(0.5745)	(0.6344)
Mobile prop			0.4586	0.6108
			(0.4090)	(0.4513)
Urban prop			0.6596	0.6903
			(0.7070)	(0.7801)
Economic Growth			0.0050	0.0059
			(0.0089)	(0.0098)
Gov effectiveness			−0.2793	−0.4142
			(0.4147)	(0.4576)
Reg quality			0.2144	0.2348
			(0.4587)	(0.5062)
_cons	−0.0257	−11.9904**	−10.4185**	2.4545***
	(0.0959	(0.9128)	(2.0690)	(2.4545)
Var(cons)	0.3291**	0.7098**	0.3061**	0.3723**
	(0.0781)	(0.1695)	(0.0734)	(0.0894)
ICC	0.2476	0.1775	0.0851	0.1017
	(0.0442)	(0.0349)	(0.0187)	(0.0219)

Notes: Standard errors are reported in parentheses. ICC represents the Intraclass correlation coefficient, Var(cons) represents the Variance of the Random Intercept, and _cons represents the constants.

*** $p < 0.01$.

** $p < 0.05, p < 0.1$.

3. Results

We report the results (Table 2) from the four multilevel models that include the null model (Model 1), the model with individual-level variables only (Model 2), the model with country-level variables only (Model 3) and the model with both individual and country-level factors (Model 4).

In Model 1, the null model includes only a random intercept for the country, with no explanatory variables. The ICC is 0.248, suggesting that nearly a quarter of the total variance in digital payment usage is attributable to differences between countries. This means that country-level factors, such as national infrastructure or policy environment, have an important role in shaping digital payment usage, even before considering individual characteristics. Fig. 1 isolates country-level variation in digital financial inclusion, revealing heterogeneities in the baseline probability of digital payment usage across nations. The ranking of countries—from South Sudan and Niger at the lower end to Mauritius and South Africa at the upper end—suggests that systemic, context-specific factors heavily shape access to digital financial services, even before accounting for individual characteristics. These results align with broader theoretical frameworks emphasising the role of macro-level determinants in financial inclusion (e.g., Gebregziabher Gebrehiwot and Makina, 2019). For instance, Demirgüç-Kunt et al. (2020) argue that gaps in digital infrastructure, such as mobile network coverage and internet penetration, create barriers to financial access in low-income countries, a pattern evident in the underperformance of fragile states like Chad and South Sudan. This resonates with Johnson and Nino-Zarazua's (2011) analysis, where disrupted institutions and fragmented markets perpetuate financial marginalisation.

The significant variation captured by the model (Fig. 1) -evident in the wide confidence intervals for some countries -suggests that unobserved institutional factors, such as regulatory quality or colonial legacies of financial exclusion (Mader, 2018), may further explain cross-national differences. These differences challenge reductionist narratives attributing financial exclusion solely to individual deficits, such as low financial literacy or poverty. While such factors matter, the null model's results reinforce Sen's (2000) argument that systemic inequalities constrain individuals' capabilities to participate in digital economies.

In Model 2, individual-level characteristics are introduced. These include *age, gender, secondary education, employment status, mobile ownership, internet access*, and *household income* quintiles. Most variables are statistically significant and aligned with expectations. Age has a positive but diminishing effect, evidenced by a significant positive coefficient on age (≈4.87) and a negative coefficient on age squared (≈−0.62), suggesting that the likelihood of using digital payments increases with age up to a point and then tapers off. *Female* has a negative association with digital payments, while having a *secondary education* is associated with an increase in digital payment use. Being employed and having internet access both significantly increase the likelihood of using digital payments. Household income also matters: higher income quintiles, particularly quintiles 4 and 5, show a clear gradient of increasing digital payment use, with quintile 5 showing the strongest effect. Notably, in Model 2, the ICC drops to 0.18, indicating that once individual characteristics are accounted for, country-level variation plays a smaller, though still meaningful, role. The drop in ICC (from 24.8 % to 18 %) suggests

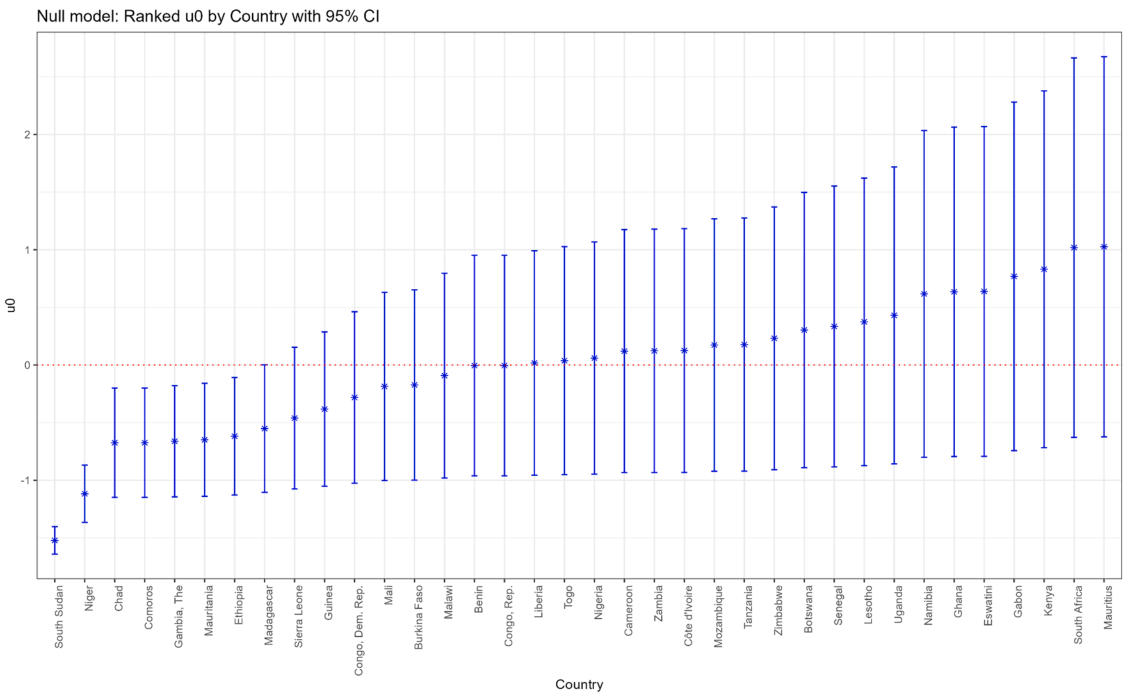

Fig. 1. Ranking of countries by u0.
Notes: This visualisation ranks countries based on estimates from a null model (u0) with 95 % confidence intervals (CIs) - reflecting baseline variation in the outcome of interest.

that a significant portion of what initially appeared to be country-level variation was driven by differences in who lives in those countries (e.g., more internet users or educated people in some countries than others).

In Model 3, only macro-level country characteristics are included in the model. Some of these variables show statistically significant effects. For example, a higher proportion of people with secondary education at the country level is strongly associated with digital payment use (≈3.59), suggesting that living in an environment with widespread education supports digital financial behaviour. The proportion employed is also positively associated (≈2.28) with digital financial inclusion. Including these country-level variables causes the ICC to drop (compared to the null model) to 0.085, showing that much of the residual country-level variation is now accounted for by observable structural characteristics. In essence, Model 3 reveals that national infrastructure and macroeconomic context play a substantial role in shaping digital payment behaviour over and above individual-level traits.

Model 4, the full model, includes both individual and country-level variables. The results here are largely consistent with those from Models 2 and 3. Individual-level predictors remain stable in magnitude and significance. Still, the bulk of country-level variance observed in Model 1 has been explained by the full set of predictors—a strong indication that digital payment use is driven by a mix of individual capability and national-level structures. The decline in the ICC from 25 % in the null model to 10 % in the full model shows that as we account for more explanatory variables, the differences between countries shrink, but do not disappear. This suggests a dual need: to empower individuals through education, employment, and digital access, while also ensuring that countries invest in supportive macroeconomic and governance environments to enable digital financial inclusion.

As a robustness check, we used alternative measures of digital financial inclusion;*mobile in-store purchases* and *internet bill payments*. The results (Table A1 in the Appendix) do not qualitatively change, reinforcing the main findings. Almost a quarter of the variance can be attributed to country-level factors, and some residual variance still exists even after accounting for individual- and country-level characteristics. We acknowledge that endogeneity biases could be present in our estimations, as digital financial inclusion and factors such as mobile ownership may influence each other. For example, while mobile ownership may facilitate the use of digital financial services, the expansion of such services may also incentivise mobile usage. Hence, we interpret the reported coefficients as associations rather than causal. Moreover, as argued by Allen et al. (2016), given the cross-sectional nature of the data, it is difficult to implement a robust identification strategy to fully address endogeneity concerns.

4. Conclusion

This study quantifies the contributions of individual and country-level factors to digital payment usage in Africa using a two-level multilevel probit model. We found that both sets of factors matter, but individual characteristics (75 % of the variance) play a more prominent role. Country-level conditions, including national education levels and internet access, also shape usage patterns. The decline in ICC values across models highlights how much variance is explained as predictors are added, confirming the value of a multilevel approach. These findings suggest that policies to boost digital financial inclusion must address both individual demographic factors as well as broader structural barriers. The model's visual output—the forest plot with ranked country effects—serves as a diagnostic tool, identifying priority geographies for targeted investment in digital financial inclusion infrastructure. For instance, the clustering of low-ranking countries in the Sahel region demonstrates the urgency of regional collaborations, such as harmonising mobile money regulations across ECOWAS states to reduce transaction costs and foster cross-border operations.

CRediT authorship contribution statement

Kingstone Nyakurukwa: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Yudhvir Seetharam:** Writing – review & editing, Supervision, Conceptualization. **Chimwemwe Chipeta:** Writing – review & editing, Supervision, Conceptualization.

Appendix

Table A1
Alternative measures of digital financial inclusion.

	Mobile in-store purchases				Internet bill payments			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age		4.9631***		4.9547***		7.2279***		7.2344***
		(0.8299)		(0.8299)		(0.7365)		(0.7364)
Age squared		−0.7335***		−0.7326***		−0.9904***		−0.9915***
		(0.1194)		(0.1194)		(0.1053)		(0.1053)
Female		−0.1349***		−0.1351***		−0.1294***		−0.1294***
		(0.0362)		(0.0362)		(0.1223)		(0.0322)
Secondary		0.3151***		0.3105***		0.5051***		0.5018***
		(0.0462)		(0.0463)		(0.0402)		(0.0403)
Income								

(continued on next page)

Table A1 (*continued*)

	Mobile in-store purchases				Internet bill payments			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Quintile 2		0.1027		0.1032		0.1570**		0.1570**
		(0.0707)		(0.0707		(0.0632)		(0.0632)
Quintile 3		0.1440**		0.1445**		0.1617***		0.1619
		(0.0678)		(0.0678)		(0.0610)		(0.0610)
Quintile 4		0.2266***		0.2277***		0.3081***		0.3086***
		(0.0649)		(0.0649)		(0.0581)		(0.0581)
Quintile 5		0.5393***		0.5414***		0.7257***		0.7269***
		(0.0612)		(0.0612)		(0.0547)		(0.0547)
Employed		0.6853***		0.6858***		0.5714		0.5712***
		(0.0472)		(0.0472)		(0.0406)		(0.0406)
Internet		0.8471***		0.8447***		0.9204***		0.9190***
		(0.0446)		(0.0446)		(0.0384)		(0.0384)
Mobile owner		0.7285***		0.7260***		0.9288***		0.9275***
		(0.0672)		(0.0672)		(0.0622)		(0.0622)
Inflation			−0.0063	−0.0074			0.0015	0.0003
			(0.0127)	(0.0135)			(0.0119)	(0.0121)
Employed Prop			−0.0646	−0.9003*			1.3323	0.7963
			(1.3962)	(1.4932)			(1.3121)	(1.3386)
Secondary prop			3.8869***	2.8870***			2.8583***	1.5772**
			(0.7244)	(0.7755)			(0.6798)	(0.6941)
Mobile prop			−0.6866	−0.7746			0.6880	0.7839
			(0.5138)	(0.5497)			(0.4836)	(0.4932)
Urban prop			1.1247	1.1752			0.1385	0.0385
			(0.8895)	(0.9515)			(0.8386)	(0.8552)
Economic Growth			0.0069	0.0069			0.0164	0.0180*
			(0.0111)	(0.0119)			(0.0105)	(0.0107)
Gov effectiveness			0.2536	0.2032			−0.2361	−0.3381
			(0.5229)	(0.5591)			(0.4913)	(0.5010)
Reg quality			0.1713	0.2064			0.1465	0.1556
			(0.5769)	(0.6171)			(0.5428)	(0.5536)
_cons	−1.2863***	−12.5366	−7.6985***	−14.9107***	−1.0324***	−17.0930***	−9.6247***	−22.1835***
	(0.0836)	(1.4235)	(2.6207)	(3.1375)	(0.0831	(1.2728)	(2.4590)	(2.8094)
Var(cons)	0.2479**	0.8053	0.4775**	0.5475**	0.2458***	0.6431**	0.4258**	0.4421**
	(0.0595)	(0.1953)	(0.1170)	(0.1335)	(0.0587	(0.1548)	(0.1029)	(0.1068)
ICC	0.1987**	0.1966	0.1267**	0.1427**	0.1973***	0.1635**	0.1146**	0.1185**
	(0.0382)	(0.0383)	(0.0271)	(0.0298)	(0.0378	(0.0329)	(0.0245)	(0.0252)

Data availability

Data will be made available on request.

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