

Determinants of Mobile Money Adoption and Formal Savings Participation in Kenya: A Bivariate Probit Approach

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ABSTRACT

This study examines the joint determinants of mobile money adoption and formal savings participation among Kenyan adults over 2011-2024, treating the two as related but distinct behaviors rather than assuming one causes the other. Despite Kenya's global leadership in digital financial innovation through platforms such as M-Pesa, mobile money adoption has grown far faster than formal savings participation. Specifically, the study tests how income, education, gender, and age determine each outcome, and whether the unobserved factors shaping the two decisions are significantly correlated. Anchored in Financial Intermediation Theory, the Technology Acceptance Model, and the Theory of Frontiers of Access Possibilities, the study adopts a repeated cross-sectional design, pooling five independent, nationally representative World Bank Global Findex survey waves (2011, 2014, 2017, 2021, and 2024). Both outcomes are modelled as binary, jointly estimated using a bivariate probit model with correlated error terms, estimated by full-information maximum likelihood on a primary pooled sample of 3,987 Kenyan adults (2014-2024), with a five-wave robustness extension (2011-2024, $n=4,987$). All ten hypotheses tested were rejected: income, education, gender, and age were each significant determinants of both outcomes, and the correlation between the two equations' unobserved determinants (ρ) was positive and highly significant ($\rho=0.223$, $p<.001$; $\rho=0.280$ in the five-wave extension), confirming that the two outcomes are jointly, not independently, determined. At the same time, formal savings participation declined even as mobile money adoption rose sharply, and more than half of mobile money adopters did not save formally, indicating that mobile money success alone has not closed the gap between financial access and financial depth. The study contributes updated, context-specific evidence on digital financial intermediation in emerging economies, with policy-relevant insight for closing Kenya's persistent gap between financial access and depth.

Keywords: mobile money, formal savings, financial inclusion, bivariate probit, Kenya

INTRODUCTION

Financial inclusion is widely regarded as a foundational driver of inclusive economic growth, poverty reduction, and household resilience (Beck et al., 2004; Demirgüç-Kunt & Klapper, 2012). Access to formal financial services enables households to manage cash flows, save securely, access credit, and buffer against economic shocks, and has been shown to reduce vulnerability and support more inclusive growth (Atkinson & Messy, 2012). This is of particular importance in Sub-Saharan Africa, where financial systems have historically been less inclusive than those elsewhere (Beck & Cull, 2013), and where financial inclusion carries a measurable relationship to poverty alleviation (Consultative Group to Assist the Poor [CGAP], 2018).

Kenya offers a distinctive case study in this respect. Formal financial inclusion rose from 26.7% in 2006 to 83.7% by 2021, driven primarily by the rapid diffusion of mobile money platforms, chiefly M-Pesa, launched by Safaricom in 2007 (Central Bank of Kenya [CBK], 2022). Registered mobile money accounts grew from roughly 19 million in 2011 to approximately 82 million by 2024 (Central Bank of Kenya, 2026), reflecting sustained growth in access even as usage patterns, the subject of this study, evolved; the Global Findex adoption rate reported below (87.5% by 2024) is the relevant measure of the share of adults actually using mobile money. Yet this remarkable expansion in access has not been matched by proportionate growth in

formal savings participation: using Global Findex data, the pooled formal savings rate among Kenyan adults fell from 30.4% in 2014 to 20.2% in 2024, even as mobile money adoption climbed from 58.4 to 87.5% over the same period. This divergence between financial access and financial depth is the empirical puzzle this study addresses.

Existing empirical work on financial inclusion in Kenya and Sub-Saharan Africa has predominantly focused on access indicators such as account ownership and credit usage, or has treated mobile money adoption as an independent predictor of formal savings rather than as a behavior that may itself be jointly determined with savings by shared unobserved factors such as financial literacy or risk attitude (Fungáčová & Weill, 2015; Zins & Weill, 2016). Kenya-specific mobile money studies — notably Jack and Suri (2014), Suri and Jack (2016), and Gürbüz (2017) — provide strong evidence that mobile money strengthens household savings and risk-sharing, but each treats mobile money as an explanatory variable for savings rather than testing directly whether the two behaviors share unobserved determinants. No study identified in this review formally tests, rather than assumes, whether mobile money adoption and formal savings participation in Kenya are jointly determined.

This study addresses that gap directly. Its general objective is to examine empirically whether mobile money adoption and formal savings participation among Kenyan adults (2011-2024) are shaped by correlated unobserved socio-economic and socio-demographic characteristics. Specifically, the study assesses how income, education, gender, and age determine each outcome, and tests whether the unobserved factors shaping the two decisions are significantly correlated. Ten null hypotheses are tested, corresponding to the effect of income, education, gender, and age on each equation (H01-H08), the correlation parameter ρ between the two equations (H09), and the joint significance of the model (H10).

LITERATURE REVIEW

Theoretical Framework

This study is grounded in Financial Intermediation Theory (FIT), tracing to Gurley and Shaw (1960) and formalized in Diamond's (1984) model of delegated monitoring, which explains how financial intermediaries — including digital platforms such as mobile money — mobilize savings and allocate credit by lowering transaction costs and mitigating information asymmetries. This is complemented by the Technology Acceptance Model (Davis, 1989), which explains the prior decision to adopt mobile money based on perceived usefulness and ease of use, and the Theory of Frontiers of Access Possibilities (Beck & de la Torre, 2007), which explains how supply-side and demand-side constraints — captured here through income, education, gender, and age — can limit both adoption and savings independently of intermediation mechanics.

Empirical Literature and Research Gap

Cross-country studies using Global Findex data consistently identify income, education, age, and gender as core determinants of financial inclusion (Fungáčová & Weill, 2015; Demirgüç-Kunt & Klapper, 2012; Camara et al., 2015). Within Sub-Saharan Africa, Zins and Weill (2016), using data from 37 countries, found income and education to exert the strongest influence on inclusion, with women, the poor, and the young disproportionately excluded. Kenya-specific mobile money research is extensive: Jack and Suri (2014) show that M-Pesa strengthened household risk-sharing and precautionary savings; Suri and Jack (2016) document long-run poverty and gender impacts; and Gürbüz (2017) finds that mobile money users in Kenya were 16-22% more likely to save formally. Regional evidence from Tanzania (Riley, 2018) and Uganda (Munyegera & Matsumoto, 2016) similarly finds mobile money associated with improved risk-sharing and household welfare.

None of these studies, however, formally test whether mobile money adoption and formal savings are related through correlated unobserved determinants. A further complication specific to Kenya is that mobile money is frequently used to facilitate informal, rotating savings and credit associations (ROSCAs, known locally as chamas), which remain a rational and widely used savings mechanism even where formal alternatives exist

(Gugerty, 2007). Accordingly, the literature gap this study addresses is twofold: limited longitudinal evidence on the relationship between mobile money adoption and formal savings in Kenya (2011-2024), and a near-total absence of studies that jointly model the two behaviors as correlated outcomes rather than treating adoption solely as an exogenous predictor of savings.

METHODOLOGY

Research Design and Data

This study adopts a repeated cross-sectional design, pooling five independent, nationally representative World Bank Global Findex survey waves for Kenya (2011, 2014, 2017, 2021, and 2024) rather than following the same individuals over time. The Global Findex is compiled in collaboration with the Gallup World Poll, with each wave published as its own edition: the 2011 and 2014 waves in Demircuc-Kunt and Klapper (2012) and its 2015 successor, the 2017 wave in Demircuc-Kunt et al. (2018), the 2021 wave in Demircuc-Kunt et al. (2022), and the 2024 wave in Klapper, Singer, Starita, and Norris (2025). The primary analysis sample pools the 2014-2024 waves (N=3,987), for which mobile money account ownership is directly measured; a five-wave robustness extension incorporates 2011 using a constructed phone-based usage proxy (N=4,987). Because each wave samples different respondents rather than following the same individuals over time, unobserved, time-invariant individual heterogeneity cannot be differenced out as it could with a true panel; the bivariate probit's correlation parameter (ρ) therefore captures shared unobserved determinants across individuals within the pooled cross-section, not a within-individual causal pathway.

The two outcomes of interest are both measured as binary variables. Mobile money adoption equals one if the respondent reports owning or using a mobile money account in the past twelve months. Formal savings equals one if the respondent reports saving at a formal financial institution or through a mobile-money-linked savings product in the past twelve months. Control variables common to both equations are income (Global Findex within-country wealth quintiles), education (secondary and tertiary-or-more dummies), gender (female=1), and age (centered, with a quadratic term). Survey-wave dummies are included in both equations to absorb common shocks and trends.

Model Specification

Because both outcomes are binary and hypothesized to share unobserved determinants, the two are estimated jointly using a bivariate probit model with correlated errors (Ashford & Sowden, 1970; Heckman, 1978), rather than as two independent single-equation probits. The latent-variable specification is:

Adoption equation

$$M_i^* = \alpha_0 + \alpha_1 \text{Female}_i + \alpha_2 \text{Age}_{ci} + \alpha_3 \text{Age}_{ci}^2 + \alpha_4 \text{Educ2}_i + \alpha_5 \text{Educ3}_i + \alpha_6 \text{IncQ2}_i + \alpha_7 \text{IncQ3}_i \\ + \alpha_8 \text{IncQ4}_i + \alpha_9 \text{IncQ5}_i + \sum_w \alpha_w \text{Wave}_{wi} + u_{1i}$$

Savings equation:

$$S_i^* = \gamma_0 + \gamma_1 \text{Female}_i + \gamma_2 \text{Age}_{ci} + \gamma_3 \text{Age}_{ci}^2 + \gamma_4 \text{Educ2}_i + \gamma_5 \text{Educ3}_i + \gamma_6 \text{IncQ2}_i + \gamma_7 \text{IncQ3}_i + \gamma_8 \text{IncQ4}_i \\ + \gamma_9 \text{IncQ5}_i + \sum_w \gamma_w \text{Wave}_{wi} + u_{2i}$$

where M_i^* and S_i^* are latent propensities toward adoption and formal savings, respectively; the observed binary outcomes are $M_i = 1 (M_i^* > 0)$ and $S_i = 1 (S_i^* > 0)$ and (u_{1i}, u_{2i}) are jointly distributed bivariate normal with mean zero, unit variances, and correlation ρ . The model is estimated by survey-weighted full-information maximum likelihood, with ρ estimated via its Fisher z-transformation. This specification nests the single-equation probit as the special case $\rho=0$; the likelihood-ratio test of that restriction is both a substantive hypothesis test (H09) and a specification test of whether a simpler single-equation approach would have been adequate.

Estimation was implemented in R using the GJRM package (Marra & Radice, 2011). Diagnostics include variance inflation factors for multicollinearity, Breusch-Pagan tests for heteroskedasticity — motivating the use of Huber-White robust standard errors throughout (White, 1980) — Pregibon's (1980) link test for functional-form misspecification, and McFadden's (1974) pseudo- R^2 alongside AIC and log-likelihood comparisons for goodness-of-fit.

RESULTS

Descriptive Patterns

Mobile money adoption rose sharply and consistently across the study period, from 58.4% of adults in 2014 to 87.5% in 2024, while formal savings participation declined over the same window, from 30.4% to 20.2% (Figure 1). The unconditional joint distribution shows formal savings participation markedly higher among mobile money adopters (20.9%) than non-adopters (3.8%), but the largest single cell in the joint distribution (51.1% of the pooled sample) is “adopted mobile money, did not save formally.”

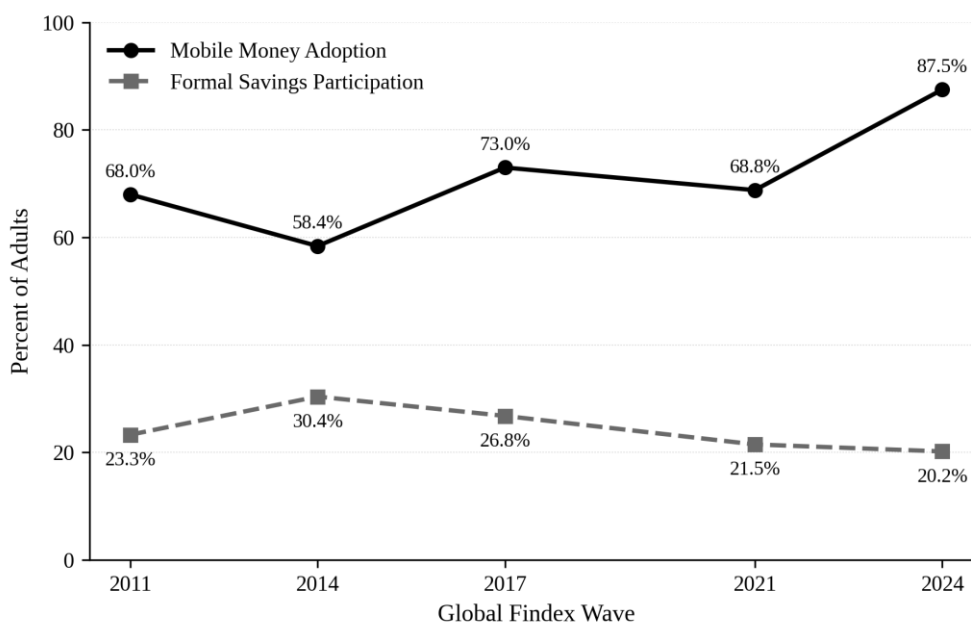


Figure 1. Mobile Money Adoption and Formal Savings Participation by Wave, Kenya 2011-2024 (Weighted)

Bivariate Probit Estimation Results

Table 1 reports the primary specification (2014-2024, $N=3,987$). Female respondents are significantly less likely than male respondents to adopt mobile money ($\beta=-0.152$, $p=0.007$) or to save formally ($\beta=-0.241$, $p<.001$). Both education categories are significant and positive in both equations, with tertiary education associated with the largest coefficient on formal savings ($\beta=1.053$, $p<.001$).

Table 1. Bivariate Probit Estimation Results, Primary Specification (2014-2024, $N=3,987$)

Variable	Adoption β (SE)	Savings β (SE)
Female	-0.152 (0.056)**	-0.241 (0.054)***
Age (centered)	0.0177 (0.0030)***	0.0137 (0.0031)***

Education: Secondary	0.513 (0.062)***	0.582 (0.069)***
Education: Tertiary+	0.497 (0.134)***	1.053 (0.113)***
Income Q5	0.582 (0.095)***	0.897 (0.098)***

Note. Robust (Huber-White) standard errors. *** $p < .001$, ** $p < .01$. $\rho = 0.223$ (SE 0.040); likelihood-ratio test of $\rho = 0$: $\chi^2 = 61.4$, $df = 1$, $p < .001$.

The correlation parameter ρ is positive and highly significant in the primary specification and remains significant, and larger, in the five-wave robustness extension incorporating 2011 ($\rho = 0.280$, $p < .001$; $N = 4,987$), confirming that mobile money adoption and formal savings share unobserved determinants across every specification estimated. Average marginal effects show tertiary education associated with a 28.5-percentage-point increase in formal savings probability, the largest single effect found in the core model. All ten hypotheses tested (H01-H10) were rejected.

Model Diagnostics, Marginal Effects, and Robustness Checks

Diagnostics for the primary specification raise no material concerns: the maximum variance inflation factor is 2.24 in both equations, well under conventional multicollinearity thresholds, and McFadden's pseudo- R^2 (0.128) is unremarkable for a probit-family model on individual-level survey data. Breusch-Pagan tests confirm heteroskedasticity in both equations, addressed throughout by Huber-White robust standard errors. Pregibon's link test is clean for the adoption equation ($p = 0.10$) but marginally significant for the savings equation ($p = 0.017$), a residual specification-quality signal disclosed here as a limitation rather than resolved through additional ad hoc terms (Table 2).

Table 2. Model Diagnostics, Primary Specification (2014-2024, $N = 3,987$)

Diagnostic	Adoption Equation	Savings Equation
Variance Inflation Factor (max)	2.24	2.24
Breusch-Pagan heteroskedasticity test	$p < .001$	$p < .001$
Pregibon link test	$p = 0.10$	$p = 0.017$
McFadden pseudo- R^2	0.128	0.128
Log-likelihood / AIC	-3,957.98	7,969.97

Average marginal effects (Table 3) show tertiary education carrying the largest single effect on formal savings (+28.5 percentage points), income quintile rising monotonically from the second to the richest quintile (+5.6 to +24.3 percentage points), and the female gap on savings at -6.5 percentage points.

Table 3. Selected Average Marginal Effects, Primary Specification

Variable	AME on Adoption (pp)	AME on Savings (pp)
Female	—	-6.5

Education: Tertiary+	–	+28.5
Income Q5 (vs. Q1)	+5.6 to +24.3 across quintiles	+5.6 to +24.3 across quintiles
Employment status (robustness)	+15.1	+12.2
Rural–urban residence (robustness)	–6.5	not significant

Three additional robustness checks were run on reduced subsamples, corresponding to Global Findex waves in which the relevant question was asked (Table 4). Employment status (2017/2021/2024, N=2,992) is strongly positive on both adoption ($\beta=0.594$, $p<.001$) and savings ($\beta=0.469$, $p<.001$), and ρ remains significant ($\rho=0.248$, $p<.001$). Rural residence (2021/2024, N=1,994) significantly reduces adoption ($\beta=-0.261$, $p=.006$) but shows no significant independent effect on savings ($\beta=-0.056$, $p=.50$) once other factors are held constant, a heterogeneity finding rather than a null result given the smaller two-wave sample; ρ remains significant ($\rho=0.246$, $p<.001$) in this subsample too. Both checks reinforce the core finding: the correlation between adoption and savings is not an artifact of the specific control set used in the primary model.

Table 4. Robustness-Check Specifications: ρ and Likelihood-Ratio Tests

Specification	N	ρ (SE)	LR test of $\rho=0$
Core, 2014–2024 (primary)	3,987	0.223 (0.040)	$\chi^2=61.4$, $p<.001$
Core, 5-wave extension (2011–2024)	4,987	0.280 (0.036)	$\chi^2=109.7$, $p<.001$
Robustness: employment status (2017/2021/2024)	2,992	0.248 (0.052)	$\chi^2=48.7$, $p<.001$
Robustness: rural–urban location (2021/2024)	1,994	0.246 (0.065)	$\chi^2=27.3$, $p<.001$

DISCUSSION

The consistently significant, positive correlation parameter ρ found across five separate specifications is this study's central empirical contribution: mobile money adoption and formal savings participation in Kenya are shaped by shared unobserved factors and should not be modelled as independent decisions, as much of the existing single-equation literature (Fungáčová & Weill, 2015; Zins & Weill, 2016) implicitly assumes. At the same time, the aggregate divergence between rising mobile money adoption and declining formal savings participation complicates any assumption that expanding digital access and deepening formal financial inclusion move together automatically. This pattern is consistent with, and extends, Kim's (2022) finding that mobile money adoption in Nairobi reduced outright exclusion without necessarily closing deeper gaps in financial engagement.

One plausible mechanism for this divergence is that mobile money's dominant documented use in Kenya is consumption-smoothing and shock resilience rather than deliberate accumulation (Yao, Shanoyan, Schwab, & Amanor-Boadu, 2023), so rising adoption does not mechanically translate into rising formal savings. This is reinforced by survey evidence that many Kenyans already consider mobile money itself a savings method, separate from chamas and bank accounts: the Central Bank of Kenya's 2024 FinAccess Household Survey found mobile money the single most-used savings method nationally (35.9%), ahead of chamas (19.7%) (FSD Kenya, 2025). Global Findex's stricter formal-savings question, saving at a financial institution or mobile-money-linked savings product, may therefore understate saving behavior that occurs inside ordinary mobile money wallets but is not reported by respondents as saving "at a financial institution." This is consistent with, though not directly testable from, this study's own finding that 51.1% of the pooled sample adopted mobile money without saving formally.

Chamas, Kenya's rotating and accumulating savings and credit associations, remain a major channel for saving that this study's formal-savings variable does not capture (Gugerty, 2007). Recent evidence suggests this channel is not shrinking as mobile money expands but increasingly uses mobile money as its transaction rail: many chamas now collect and disburse member contributions via mobile money, and better-governed groups, those with more accountable, bank-linked fund management, mobilize significantly more savings from their members (Agesa & Agesa, 2025). This suggests mobile money and informal group savings are complements in practice rather than substitutes, further complicating any expectation that mobile money adoption should mechanically raise the formal savings rate measured here, and pointing to informal-formal savings linkages as a priority for future research.

The socio-demographic results also map onto the study's three guiding theories: education and income produce the largest marginal effects found in the analysis, while the persistent gender gap in both outcomes is consistent with the structural constraints the Theory of Frontiers of Access Possibilities predicts.

Three variables plausibly relevant to both outcomes were not included as full-sample controls, for a data-availability reason each. Employment status and rural–urban location are asked only in a subset of Global Findex waves and are therefore reported above as reduced-subsample robustness checks (Table 4) rather than core predictors. Financial literacy has no individual-level measure in the Global Findex waves pooled here; this is addressed by design rather than by omission, since this study's central methodological choice, jointly estimating adoption and savings with a correlated error term rather than as independent single-equation models, exists precisely to capture the influence of unobserved factors such as financial literacy without requiring them as observed regressors. Banking-infrastructure access (for example, distance to a bank branch or agent density) is similarly unavailable in this dataset and remains an open limitation, disclosed below.

LIMITATIONS

This study has four main limitations. First, Global Findex is a repeated cross-section, not a panel; the correlation ρ reflects shared unobserved determinants across individuals within each wave, not within-individual dynamics over time, so findings should be read as correlational rather than causal. Second, employment status and rural–urban location are available only in a subset of waves and are therefore reported as reduced-subsample robustness checks rather than full-sample core predictors. Third, financial literacy and banking-infrastructure access are not measured in the Global Findex waves pooled here; the former is addressed by the bivariate probit's correlated-error design rather than as an observed control, while the latter remains an open data gap. Fourth, formal savings is measured by self-report and, as the discussion above notes, may understate saving behavior that respondents do not associate with a formal financial institution, such as saving inside a mobile money wallet.

CONCLUSION AND POLICY RECOMMENDATIONS

This study set out to test, rather than assume, whether mobile money adoption and formal savings participation in Kenya are jointly determined. Using a bivariate probit model estimated on pooled Global Findex data (2011–2024), it finds that they are: the correlation between the two equations' unobserved determinants is positive

and highly significant across every specification estimated, while income, education, gender, and age each significantly shape both outcomes. At the same time, formal savings participation has declined even as mobile money adoption has become near-universal, indicating that Kenya's celebrated mobile money success has not, on its own, closed the gap between financial access and financial depth.

These findings suggest that Kenya's National Financial Inclusion Strategy should continue to track formal-savings depth alongside access-side indicators, that the persistent gender gap in both adoption and formal savings warrants dedicated, gender-responsive programming, and that formal-savings products should be designed to link to, rather than compete with, informal savings mechanisms such as chamas that Kenyans already trust.

Ethical Considerations

This study relied exclusively on secondary, publicly available, de-identified data from the World Bank's Global Findex Database. No primary data collection, survey administration, or direct contact with human subjects was undertaken by the authors; accordingly, no ethical approval was required for this study.

Conflict of Interest: The authors declare no conflict of interest.

Data Availability

The data underlying this study are publicly available from the World Bank Global Findex Database (<https://www.worldbank.org/en/publication/globalfindex>), and can be freely accessed by any interested researcher.

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