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Mobile Money Penetration and Financial Inclusion Outcomes in Sub-Saharan Africa: A Multi-Country Panel Analysis

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ABSTRACT

This study examines the relationship between mobile money penetration and financial inclusion outcomes across 45 Sub-Saharan African countries over the period 2013 to 2023, using an unbalanced panel dataset constructed from the IMF Financial Access Survey, World Development Indicators, and Worldwide Governance Indicators. Three distinct dimensions of mobile money penetration are examined: registered account ownership, active account usage, and transaction value as a share of GDP. Financial inclusion is operationalised across four outcome variables: ATM density, bank branch density, deposits to GDP, and loans to GDP. Two-way fixed effects estimation with Driscoll-Kraay standard errors is employed to address heteroskedasticity, serial correlation, and cross-sectional dependence. The Hausman test strongly favours fixed effects over random effects ($\chi^2 = 454.73$, $p < 0.001$). The results indicate that registered account ownership and transaction value produce no statistically significant effects on any financial inclusion outcome. Active account usage, by contrast, is positively associated with ATM density ($\beta = 0.0038$, $p = 0.031$) and loans to GDP ($\beta = 0.0042$, $p = 0.031$), with a marginally significant positive effect on deposits to GDP ($\beta = 0.0056$, $p = 0.084$). These findings hold under Driscoll-Kraay correction. The evidence suggests that the usage dimension of mobile money, rather than account ownership or transaction intensity, is the operationally relevant mechanism through which mobile money contributes to financial sector development in Sub-Saharan Africa.

1. Introduction

Sub-Saharan Africa has, over the past two decades, become the most studied region in the world for mobile money. The reasons are straightforward: conventional banking infrastructure remains thin across much of the continent, mobile phone penetration expanded rapidly from the mid-2000s onwards, and a handful of early deployments, particularly M-Pesa in Kenya, produced welfare effects large enough to generate a sustained empirical literature (Abiona & Koppensteiner, 2022; Coffie et al., 2020). By 2023, Sub-Saharan Africa accounted for the largest share of global registered mobile money accounts, with the GSMA reporting over 800 million registered accounts on the continent (GSMA, 2023). The policy interest has kept pace: financial inclusion targets embedded in the African Union's Agenda 2063 and in individual country development strategies treat mobile money expansion as a primary lever for broadening economic participation.

The empirical literature has not, however, kept pace with the conceptual demands of this policy environment. Most multi-country studies examine mobile money through a single indicator, typically registered account ownership, and map it onto a single financial inclusion outcome, typically account ownership at the national level (Coffie et al., 2020; Drama & Senou, 2025). This produces an analytical picture that equates the opening of a mobile money account with financial inclusion, which the evidence increasingly suggests is misleading. Account ownership is a supply-side access metric. What the development agenda actually concerns is whether people engage with financial services in ways that improve their welfare, build financial sector depth, and support economic intermediation. These are usage and quality dimensions, not access dimensions, and they require different measurement strategies (Joia & Cordeiro, 2021; Siano et al., 2020).

A related gap concerns the decomposition of mobile money penetration itself. Registered accounts, active accounts, and transaction values capture fundamentally different economic phenomena. A country where 80% of adults have registered mobile money accounts but only 20% transact regularly has a very different financial inclusion profile from one where 40% are registered and all of them transact weekly. Whether these distinctions matter empirically for financial sector development outcomes has not been systematically tested in a multi-country panel framework covering Sub-Saharan Africa across a period long enough to observe meaningful variation. This study addresses both gaps. Using an unbalanced panel of 45 Sub-Saharan African countries from 2013 to 2023, constructed from the IMF Financial Access Survey (IMF, 2023), World Development Indicators (World Bank, 2024), and Worldwide Governance Indicators (World Bank WGI, 2024), the study estimates the relationship between three alternative measures of mobile money penetration and four financial inclusion outcomes. The outcome variables, ATM density, bank branch density, deposits to GDP, and loans to GDP, capture financial infrastructure, savings mobilisation, and credit intermediation separately, rather than treating financial inclusion as a single phenomenon.

The theoretical motivation draws on two frameworks. Financial intermediation theory, as elaborated in the tradition of Goldsmith (1969), McKinnon (1973), and subsequent empirical work by Levine (2005), holds that the breadth and depth of financial intermediation are central determinants of capital accumulation and economic growth. Mobile money's potential contribution within this framework is specific: by lowering the transaction costs of financial participation for previously excluded populations, it may expand the deposit base from which lending can be funded and extend the reach of credit markets beyond the geographic constraints of branch banking. The digital financial inclusion literature, drawing on cross-country and micro-level evidence, adds a behavioural layer, documenting the mechanisms through which digital finance translates into household savings, investment, and shock resilience (Joia & Cordeiro, 2021; Siano et al., 2020; Tinta et al., 2022). The study makes three contributions. First, it disaggregates mobile money penetration into its three measurable dimensions and tests each against multiple financial inclusion outcomes simultaneously, producing a more complete empirical picture than single-indicator studies. Second, it employs Driscoll-Kraay standard errors specifically chosen for their robustness to the cross-sectional dependence that is characteristic of African panel data, where shared commodity price shocks, regional policy spillovers, and common economic trends generate correlated disturbances across countries (Driscoll & Kraay, 1998). Third, the finding that active account usage, rather than ownership or transaction volume, drives financial inclusion outcomes has policy implications that distinguish this research from studies that conflate adoption with use.

2. Literature Review

2.1 Mobile Money and Financial Sector Development

The relationship between mobile money and financial inclusion has been examined from several angles. At the household level, Abiona and Koppensteiner (2022) exploit the expansion of Tanzania's mobile money agent network as a quasi-natural experiment, finding that mobile money adoption reduces the probability of falling below the poverty line during negative rainfall shocks by 14.6 percentage points, with account ownership tripling from 11% to 32% over the period of network expansion. Adbi and Natarajan (2023), drawing on survey data from 74 low- and middle-income countries, document a 154% increase in saving probability for mobile money-using microenterprises, with effects differentiated by gender and bank account access. At the aggregate level, Coffie et al. (2020) use a panel of 11 Sub-Saharan African countries to show that mobile payment transactions are positively associated with formal account ownership, while Drama and Senou (2025) find heterogeneous effects of digital technologies on banking inclusion across 45 African countries, with significant variation by country income level and existing financial infrastructure. These studies collectively establish the plausibility of a mobile money-financial inclusion relationship. What they do not establish is whether the relevant pathway runs through account registration, active engagement, or transaction intensity, and whether the outcome is access, intermediation depth, or credit penetration. The present study addresses this gap directly.

2.2 The Access-Usage Distinction in Financial Inclusion Research

Financial inclusion is increasingly recognised as a multidimensional construct that cannot be reduced to account ownership. Joia and Cordeiro (2021), drawing on a Delphi study of Brazilian FinTech professionals, identify access, usage, affordability, and quality as the core dimensions of financial inclusion, arguing that supply-side access indicators dominate measurement frameworks at the expense of demand-side engagement measures. Siano et al. (2020), in a meta-synthesis of mobile banking evidence from Nigeria and Sub-Saharan Africa, document a similar discrepancy between account registration rates and actual usage depth. The dormant account problem is well-documented in African mobile money markets: GSMA (2023) reports that the gap between registered and active accounts across Sub-Saharan Africa implies a large population of technically included but practically excluded individuals.

The distinction between registered and active mobile money accounts is therefore not merely definitional. It reflects a substantive difference in the nature of financial engagement, with documented implications for welfare outcomes. Tetteh (2023) finds that digital lending development reduces food and health deprivation in rural Kenya, with effects concentrated in areas where active usage, not just account penetration, is higher. Kim and Duvendack (2024) document that mobile banking loans in Kenya, which require active account engagement, generate positive short-term liquidity effects alongside significant debt accumulation risks. In both cases, the relevant variable is active engagement rather than account ownership. No multi-country panel study has, to the authors' knowledge, systematically tested whether this micro-level distinction between registered and active accounts has macro-level implications for financial sector development indicators across Sub-Saharan Africa.

2.3 Panel Estimation in African Financial Inclusion Research

The panel econometrics of African financial inclusion studies present well-known challenges. Cross-sectional dependence arises from common external shocks, particularly commodity price cycles, drought events, and regional policy contagion, that generate correlated disturbances across countries (Pesaran, 2015). Standard clustered standard errors address heteroskedasticity and autocorrelation but do not account for this cross-sectional correlation. Driscoll and Kraay (1998) develop a covariance estimator that addresses all three problems simultaneously and is appropriate for panel datasets where T is moderate and cross-sectional dependence is expected. Hoechle (2007) documents the implementation and properties of this estimator in the context of development economics panel studies. Despite the well-known appropriateness of Driscoll-Kraay standard errors for African panel data, they remain less commonly used in the financial inclusion literature than clustered standard errors, and multi-country studies rarely test explicitly for cross-sectional dependence before choosing their covariance estimator.

2.4 Research Gaps

Three specific gaps motivate this study's design. First, most multi-country African panel studies use registered account ownership as the sole mobile money indicator, conflating adoption and active use. Second, financial inclusion outcomes are typically measured through a single aggregate indicator rather than disaggregated by access, intermediation depth, and credit penetration. Third, the use of standard errors appropriate for African cross-country panels with cross-sectional dependence is less consistent than the literature's methodological standards would require. This study addresses all three gaps through a dataset that includes three mobile money measures, four financial inclusion outcomes, and Driscoll-Kraay estimation validated by a prior Hausman test for model selection.

3. Data and Variables

3.1 Data Sources

The dataset is constructed by merging three publicly available sources. The IMF Financial Access Survey (FAS) provides annual country-level data on mobile money accounts and traditional banking infrastructure for up to 189 countries. The analysis uses the 2013 to 2023 period for Sub-Saharan African economies, yielding a maximum of 45 countries and 11 annual observations per country. The World Development Indicators (WDI) provide macroeconomic control variables at annual frequency. The Worldwide Governance Indicators (WGI), specifically the Regulatory Quality estimate, provide institutional quality data. Country name harmonisation across the three sources was carried out through a country mapping protocol applied during dataset merging.

3.2 Variable Construction

Mobile money penetration variables: Three measures are constructed from the IMF FAS. *Registered accounts* is measured as registered mobile money accounts per 1,000 adults. This captures the stock of accounts opened, irrespective of whether they are used. Given the right-skewed distribution of this variable (*mean = 933.7, max = 3,943.8*), it is log-transformed as ln(registered accounts + 1) in all regression specifications. *Active accounts* is measured as active mobile money accounts per 1,000 adults, defined by the IMF FAS as accounts used at least once in the previous 90 days. This captures the flow of active financial participation. Its mean of 416.98 against a registered account mean of 933.68 implies that approximately 55% of registered accounts are active, reflecting the dormant account gap documented in the GSMA literature. *Transaction* *value* is measured as the total value of mobile money transactions as a percentage of GDP. This captures the economic intensity of mobile money use, distinct from account penetration.

Financial inclusion outcome variables: Four outcomes are used, selected to capture different dimensions of financial sector development. *ATM density* is measured as ATM machines per 100,000 adults. This proxies financial infrastructure reach and physical access to payment and cash services. *Bank branch density* is measured as commercial bank branches per 100,000 adults. This captures traditional banking network extent. *Deposits to GDP* is the ratio of outstanding deposits to GDP. This proxies savings mobilisation depth. *Loans to GDP* is the ratio of outstanding loans to GDP. This proxies credit intermediation depth.

Control variables: The following controls are drawn from the WDI and WGI: *ln(GDP per capita)* is the log of constant 2015 US dollar GDP per capita, controlling for income-related differences in financial sector depth. *Internet users* is the share of the population using the internet, controlling for digital infrastructure. *Mobile subscriptions* is mobile cellular subscriptions per 100 people, controlling for telecommunications penetration. *Inflation* is the annual consumer price index inflation rate, controlling for macroeconomic instability. *Regulatory quality* is the WGI Regulatory Quality estimate (ranging from approximately -2.5 to +2.5), controlling for the institutional environment. Following the VIF diagnostic results reported in Section 4, urban population was excluded from the final specification due to its contribution to multicollinearity when combined with internet users and mobile subscriptions ($VIF = 12.63$ before exclusion), despite the remaining controls showing acceptable VIF values of 1.03 to 2.83 when the intercept is included in the calculation.

3.3 Sample Description

The master dataset contains 462 country-year observations across 45 countries for the period 2013–2023. Because reporting coverage differs across mobile money indicators, the panel is unbalanced and the number of observations available for estimation varies across model specifications. Missing data patterns differ substantially across mobile money variables: registered accounts are missing in 25.3% of observations, active accounts in 35.7%, and transaction value in 34.2%, reflecting uneven IMF FAS reporting coverage across the continent, particularly in earlier years and for smaller economies. Control variables sourced from WDI are complete for all 462 observations. The regression sample for the active accounts specification, which serves as the primary model, comprises 274 observations across 36 countries.

3.4 Missing Data and Unbalanced Panel

The panel is unbalanced due to incomplete reporting in the IMF Financial Access Survey. While the master dataset contains 462 country-year observations across 45 countries during 2013–2023, data availability varies across mobile money indicators. Consequently, the effective estimation sample differs by specification. The registered accounts models are estimated using 321 observations from 38 countries, the active accounts models use 295 observations from 37 countries, and the transaction value models use 302 observations from 35 countries. Missing observations are concentrated in the early years of the sample and among smaller economies where mobile money reporting is less consistent. The fixed-effects estimator accommodates unbalanced panels, allowing all available information to be retained without requiring balanced country coverage.

4. Methodology

4.1 Baseline Specification

The baseline estimating equation is:

$$FI_it = \alpha + \beta(MM_it) + \gamma(Controls_it) + \mu_i + \lambda_t + \varepsilon_it$$

In the equation, FI_it is a financial inclusion outcome for country i in year t, MM_it is one of the three mobile money penetration measures, $Controls_it$ is the vector of macroeconomic and institutional controls, μ_i is an unobserved country fixed effect absorbing time-invariant country heterogeneity, λ_t is a year fixed effect absorbing common time trends, and ε_it is the idiosyncratic error term. Four separate models are estimated for each mobile money measure, one for each dependent variable, yielding twelve models in total.

4.2 Model Selection: Hausman Test

The choice between fixed effects and random effects is determined by the Hausman (1978) test, which examines whether the unobserved country-specific effects are correlated with the regressors. If they are, random effects estimates are inconsistent and fixed effects is the appropriate estimator. The test statistic is:

$$H = (b_FE - b_RE)'[V(b_FE) - V(b_RE)]^{(-1)}(b_FE - b_RE)$$

It follows an asymptotic chi-squared distribution under the null hypothesis of no systematic difference between estimators. The test was implemented for the ATM density model using the active accounts specification. The result was H = 454.73 with $p < 0.001$, strongly rejecting the null hypothesis and confirming that fixed effects is the consistent and preferred estimator. Additionally, the F-test for poolability, which tests whether country fixed effects are jointly significant, returns *F = 98.11* with *p = 0.000*, further ruling out pooled OLS. Both findings support the two-way fixed effects specification throughout.

4.3 Standard Error Correction

African cross-country panels are susceptible to cross-sectional dependence, arising from shared commodity cycles, regional shocks, and policy spillovers that affect multiple countries simultaneously. Standard clustered standard errors address within-cluster heteroskedasticity and autocorrelation but do not account for cross-sectional correlation. Driscoll-Kraay standard errors (Driscoll & Kraay, 1998) address all three problems through a non-parametric covariance estimator that is robust to heteroskedasticity, serial correlation up to the bandwidth lag, and cross-sectional dependence. All main results are reported with both clustered standard errors and Driscoll-Kraay standard errors to illustrate the robustness of significance levels to the choice of covariance estimator.

4.4 Multicollinearity Diagnostics

Variance Inflation Factors were computed for the control variable set. The initial calculation without a constant term produced inflated VIF values for GDP per capita (*VIF = 23.36*) and mobile subscriptions (*VIF = 17.67*), which is a known artefact of omitting the intercept from the VIF computation. After including the constant term, following the procedure of O'Brien (2007), all VIF values were acceptable: ln(GDP per capita) = 2.34, internet users = 2.83, mobile subscriptions = 2.51, inflation = 1.03, and regulatory quality = 1.91. No multicollinearity corrections to the model specification were required.

4.5 Outlier and Distributional Diagnostics

IQR-based outlier detection identified 77 outliers in ATM density, 52 in branch density, 38 in deposits to GDP, 35 in loans to GDP, and 4 in active accounts. These observations reflect genuine economic heterogeneity across Sub-Saharan African economies, with financial sector leaders such as South Africa, Mauritius, Kenya, and Botswana naturally exhibiting substantially higher financial infrastructure indicators than fragile states. Given that the two-way fixed effects estimator controls for time-invariant country characteristics, these observations are analytically appropriate to retain. No winsorisation is applied in the main specification.

5. Results

5.1 Descriptive Statistics

Table 1. Descriptive Statistics

Variable	*N*	*Mean*	*SD*	*Min*	*P25*	*Median*	*P75*	*Max*
Mobile Money								
Registered accounts (per 1,000)	345	933.68	850.73	0.056	237.73	688.33	1,373.96	3,943.78
Active accounts (per 1,000)	297	416.98	398.75	0.032	65.71	292.34	658.61	1,879.46
Transaction value (% GDP)	304	28.09	36.99	0.000	0.985	13.15	43.21	216.26
Financial Inclusion								
ATM density (per 100,000)	449	14.66	18.87	0.363	3.986	6.536	14.08	88.65
Branch density (per 100,000)	456	6.969	8.593	0.605	2.772	4.220	6.580	53.10
Deposits to GDP (%)	428	36.60	41.07	5.175	16.63	24.90	38.32	284.86
Loans to GDP (%)	433	25.59	32.47	0.625	10.79	16.02	28.75	239.41
Controls								
ln (GDP per capita)	454	7.253	0.910	5.539	6.605	7.096	7.706	9.877
Internet users (%)	455	25.65	19.31	1.042	10.00	21.02	36.27	86.00
Mobile subscriptions (per 100)	456	86.12	35.13	18.93	59.57	84.09	107.50	179.03
Inflation (%)	452	10.16	36.02	-6.687	1.787	4.777	8.303	557.20
Regulatory quality	440	-0.622	0.575	-2.001	-0.962	-0.693	-0.369	1.137

Note: Sample period 2013-2023. 45 Sub-Saharan African countries in the full dataset. Regression samples vary across specifications due to mobile money variable coverage.

The descriptive statistics reveal two features worth noting before the regression results are discussed. First, the gap between registered and active accounts is substantial: average registered accounts per 1,000 adults (933.68) are more than twice the average active accounts per 1,000 adults (416.98). This gap, consistent with GSMA reporting on dormant accounts across Sub-Saharan Africa, provides the empirical motivation for testing the registered-versus-active distinction formally. Second, financial inclusion outcomes exhibit pronounced heterogeneity: ATM density ranges from 0.36 to 88.65 per 100,000 adults, deposits to GDP from 5.2% to 284.9%, and loans to GDP from 0.6% to 239.4%. This variation is driven primarily by structural differences between financial sector leaders such as South Africa, Mauritius, and Botswana and lower-income economies with nascent financial systems.

5.2 Correlation Matrix

Table 2. Correlation Matrix

	Active acc.	*ATM*	*Branch*	*Deposits*	*Loans*	*ln(GDP pc)*	*Internet*	*Mobile subs*	*Inflati on*	*Reg. quality*
Active accounts	1.000	0.085	-0.063	0.029	0.080	0.124	0.287	0.312	0.062	0.180
ATM density		1.000	0.754	0.296	0.279	0.788	0.739	0.591	-0.079	0.647
Branch density			1.000	0.353	0.270	0.621	0.588	0.450	-0.065	0.488
Deposits/GDP				1.000		0.295	0.296	0.334	-0.051	0.325
Loans/GDP					1.000	0.279	0.279	0.329	-0.104	0.274
ln(GDP per capita)						1.000	0.645	0.525	-0.029	0.528
Internet users							1.000	0.687	-0.033	0.559
Mobile subscriptions								1.000	-0.105	0.685
Inflation									1.000	-0.188
Reg. quality										1.000

Note: Pearson correlations. Bold indicates the variable of primary interest.

The simple correlations between active accounts and the financial inclusion outcomes are modest: 0.085 with ATM density, 0.029 with deposits to GDP, and 0.080 with loans to GDP. Branch density shows a weak negative correlation (-0.063). That the fixed effects regressions reveal significant relationships for ATM density and loans to GDP despite these low raw correlations suggests that country-specific unobservable were masking the within-country relationship in the raw data, which is precisely what fixed effects estimation is designed to address.

5.3 Fixed Effects Results: Main Models

Table 3. Two-Way Fixed Effects Results: Active Accounts as Main Independent Variable

	(1) ATM Density	*(2) Branch Density*	*(3) Deposits/GDP*	*(4) Loans/GDP*
Active accounts	**0.0038** **	0.0003	**0.0056***	**0.0042** **
	(0.0014)	(0.0006)	(0.0032)	(0.0020)
ln(GDP per capita)	-4.790*	-0.484	4.426	-6.183
	(1.583)	(0.734)	(6.462)	(5.283)
Internet users	0.0722***	-0.0098	0.0302	0.0852
	(0.0105)	(0.0131)	(0.0906)	(0.0780)
Mobile subscriptions	-0.0165	0.0069	0.0408	0.0401

	(0.0150)	(0.0078)	(0.0545)	(0.0423)
Inflation	-0.0029**	-0.0015	-0.0248	-0.0108
	(0.0013)	(0.0013)	(0.0371)	(0.0108)
Regulatory quality	0.6331	-0.4218	2.408	9.108**
	(2.431)	(0.763)	(5.428)	(4.335)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	274	272	264	264
Countries	36	36	35	35
Within R^2	0.044	0.081	0.031	0.040

*Standard errors in parentheses are Driscoll-Kraay. *** p<0.01, ** p<0.05, * p<0.10*

The results for the active accounts specification reveal a clear pattern. Active mobile money account usage is positively and significantly associated with ATM density ($\beta = 0.0038, p < 0.05$) and loans to GDP ($\beta = 0.0042, p < 0.05$), with a marginally significant positive effect on deposits to GDP ($\beta = 0.0056, p < 0.10$). Branch density shows no statistically significant relationship with active account penetration. In the loans to GDP model, regulatory quality is significant and positive ($\beta = 9.108, p < 0.05$), indicating that better-regulated financial environments are associated with deeper credit intermediation, consistent with evidence from Sampat et al. (2023) on how regulatory quality shapes financial sector outcomes. Inflation is negatively associated with ATM density ($\beta = -0.0029, p < 0.05$) under Driscoll-Kraay correction, suggesting macroeconomic instability constrains financial infrastructure investment.

5.4 Robustness Results: Registered Accounts and Transaction Value

Table 4. Fixed Effects Results by Mobile Money Measure: Coefficient on Mobile Money Variable

Dependent Variable	*Registered Accounts*	*Active Accounts*	*Transaction Value*
ATM density	0.578 (*p=0.193*)	**0.0038** (*p=0.031*)**	-0.012 (*p=0.573*)
Branch density	0.571 (*p=0.320*)	0.0003 (*p=0.610*)	0.028 (*p=0.124*)
Deposits/GDP	0.580 (*p=0.790*)	**0.0056** (*p=0.084*)*	0.089 (*p=0.156*)
Loans/GDP	0.473 (*p=0.648*)	**0.0042** (*p=0.031*)**	0.021 (*p=0.671*)
Observations	321	274	283
Countries	38	36	33

*All models include country and year fixed effects with Driscoll-Kraay standard errors. Significance: **p<0.05; *p<0.10*

Neither registered accounts nor transaction value produces a statistically significant coefficient for any of the four outcome variables. The absence of a registered account effect is consistent with the interpretation that account registration alone, without active financial engagement, does not translate into broader financial sector development. The absence of a transaction value effect is somewhat more unexpected but may reflect the concentration of high-value transactions among a relatively small share of users whose activity does not represent broad-based inclusion gains.

5.5 Driscoll-Kraay vs Clustered Standard Errors

Table 5. ATM Density Model: Comparison of Standard Error Estimators

Variable	*Clustered SE*	*p-value*	*Driscoll-Kraay SE*	*p-value*
Active accounts	0.0014	0.031	0.0014	0.007
ln(GDP per capita)	2.584	0.065	1.583	0.003

Internet users	0.032	0.024	0.011	0.000
Mobile subscriptions	0.017	0.332	0.015	0.273
Inflation	0.004	0.509	0.001	0.031
Regulatory quality	4.873	0.908	2.431	0.795

The Driscoll-Kraay estimator produces uniformly tighter standard errors than the clustered estimator for most variables in the ATM density model, and the active accounts coefficient remains significant at the 1% level ($p = 0.007$) under Driscoll-Kraay correction compared to 5% under clustered standard errors. The improvement in precision reflects the efficiency gains from accounting for cross-sectional dependence as an additional source of information about residual covariance structure, rather than treating it as noise to be corrected. The stability of the active accounts coefficient across both covariance estimators provides additional confidence in its robustness.

5.6 Model Diagnostics

The Hausman test statistic of 454.73 ($p < 0.001$) strongly rejects random effects in favour of fixed effects. The F-test for poolability is equally emphatic: $F(45, 222) = 98.11$, $p = 0.000$, rejecting pooled OLS. Within R-squared values range from 0.018 to 0.174 across models. These values appear low in absolute terms but are expected in fixed effects models that absorb substantial between-country variation through entity effects. The within R-squared measures explanatory power over within-country time variation only, which is the relevant quantity for causal inference in this setting.

6. Discussion

6.1 The Usage Distinction and Its Implications

The central finding of this study is that the relationship between mobile money penetration and financial inclusion outcomes depends on which dimension of mobile money is measured. Registered accounts, which is the indicator most commonly used in multi-country financial inclusion studies, shows no significant association with any of the four outcome variables after controlling for country and year fixed effects. Active accounts, which capture whether people are actually using mobile money services, shows positive and significant associations with ATM density and loans to GDP, with marginal support for deposits to GDP. This pattern is not difficult to explain. Account registration is a threshold event that may or may not reflect meaningful financial engagement. The IMF FAS definition of active accounts, requiring at least one transaction in the previous 90 days, provides a more operationally meaningful measure of financial participation. That ATM density responds positively to active account usage suggests a complementarity between mobile money and traditional banking infrastructure: as more people engage actively with mobile money, demand for associated cash-in and cash-out infrastructure, and for services that link mobile wallets to physical cash networks, increases. This is the opposite of a substitution story, in which mobile money replaces the need for ATMs. The correlation matrix provides preliminary evidence for this interpretation: the simple correlation between active accounts and ATM density is 0.085, weak but positive, and the fixed effects results confirm a within-country positive relationship once time-invariant country characteristics are controlled.

The positive relationship between active accounts and loans to GDP is consistent with financial intermediation theory. If active mobile money usage generates a broader deposit base as users accumulate balances, and if this deposit accumulation is channelled through the formal financial system into lending, then credit intermediation should deepen as active mobile money penetration rises. The marginal significance of the deposits to GDP coefficient ($p = 0.084$) means this second step of the mechanism is supported only weakly, which may reflect the partial integration of mobile money float into the formal deposit base in some countries, or simply a longer lag between mobile money usage and deposit base formation than the 2013 to 2023 window captures.

6.2 What Transaction Value Does Not Explain

The absence of any significant effect for transaction value as a share of GDP is an equally important finding, though one that deserves careful interpretation. Transaction value measures the aggregate economic intensity of mobile money use and is likely concentrated among heavy users: merchants, businesses, and individuals processing remittances and payroll. If high transaction volumes are driven by a relatively small number of high-frequency users, the aggregate measure may not proxy for broad-based financial participation at all. The standard deviation of transaction value (37.0% around a mean of 28.1% of GDP) and the extreme maximum (216.3% in one country-year observation) are consistent with this interpretation. A small number of countries with highly developed mobile money ecosystems, most likely Kenya, Tanzania, and Uganda, drive the right tail of the transaction value distribution, and the within-country variation in transaction value may not reflect the same broadening of participation that active account growth represents.

6.3 Branch Density: The Non-Result

Bank branch density shows no significant relationship with any mobile money measure. This is broadly consistent with evidence from the existing literature: branch networks expand and contract in response to the economics of physical banking infrastructure rather than in direct response to mobile money penetration. Physical branches serve different populations and different transaction types from mobile money agents. The absence of a substitution effect, in which mobile money expansion would be expected to reduce branch density if the two were competing for the same users, is also informative. It suggests that mobile money and conventional banking infrastructure in Sub-Saharan Africa are neither substitutes nor complements in the branch network dimension, operating largely independently of each other at the macro level.

6.4 Regulatory Quality and Credit Markets

The significant positive coefficient on regulatory quality in the loans to GDP model ($\beta = 9.108, p < 0.05$) adds a finding beyond the primary mobile money question. Better-regulated financial environments are associated with deeper credit penetration. This is consistent with extensive theoretical and empirical evidence on the role of institutional quality in financial development (Demetriades & Law, 2006; Levine, 2005) and with the specific evidence on regulatory gaps in African digital credit markets documented by Johnen et al. (2021) and Kim and Duvendack (2024). The co-significance of active accounts and regulatory quality in the loans to GDP model suggests these are independent channels: mobile money usage deepens credit access through a different pathway from formal regulatory improvement, though both matter.

6.5 Limitations

Several limitations apply. The panel is unbalanced, with 11 of 37 countries in the active accounts sample having complete 11-year observations and the remainder ranging from 1 to 10 years. Mobile money reporting in the IMF Financial Access Survey is incomplete for some smaller economies, particularly during the early years of the study period. As a result, the master dataset of 462 country-year observations is reduced to 321 observations for the registered accounts models, 295 observations for the active accounts models, and 302 observations for the transaction value models. Although fixed-effects estimation remains valid for unbalanced panels, the reduction in sample size may lower statistical power and limit the precision of coefficient estimates. The within R-squared values are modest, indicating that country-year fixed effects absorb most of the variation in financial inclusion outcomes and that the mobile money variables explain relatively little of the residual within-country variation over time. This is a known limitation of highly macro-level panel analysis, where financial sector development moves slowly relative to annual data frequency. Finally, while the Driscoll-Kraay estimator addresses cross-sectional dependence in the covariance structure, the study does not implement instrumental variable or System GMM estimation, and reverse causality from financial sector development to mobile money adoption cannot be fully ruled out from the current design.

7. Conclusion

This study examined the relationship between mobile money penetration and financial inclusion outcomes across 45 Sub-Saharan African countries from 2013 to 2023 using two-way fixed effects panel regression with Driscoll-Kraay standard errors. The analysis found that the distinction between registered account ownership, active account usage, and transaction intensity matters for empirical results in ways that most multi-country studies have not examined. Registered accounts and transaction value produce no statistically significant effects on financial inclusion outcomes. Active account usage is positively and significantly associated with ATM density and loans to GDP, with marginal evidence for deposits to GDP. These results are robust to the choice of covariance estimator and survive Hausman test verification of the fixed effects specification.

The practical implication is that financial inclusion policies oriented toward account registration targets may be insufficient if active usage does not follow. In Sub-Saharan Africa, the gap between registered and active mobile money accounts is substantial, averaging roughly 55% of registered accounts being active across the sample period. Strategies that incentivise the transition from dormant account holding to regular financial engagement, through agent training, product design, financial capability interventions, and regulatory environments that encourage competitive and affordable mobile money services, are more likely to generate the financial sector development effects that inclusion policy seeks. The findings also raise a methodological point for future research. Standard errors appropriate for cross-country African panels, specifically those addressing cross-sectional dependence, are more conservative than clustered standard errors for some coefficients and less conservative for others. The active accounts coefficient survives and in fact strengthens under Driscoll-Kraay correction, which is reassuring. But the relative frequency with which published multi-country African panel studies use clustered standard errors without testing for cross-sectional dependence suggests this dimension of methodological rigour deserves more attention. Future research should examine whether the active accounts-ATM density and active accounts-loans to GDP relationships hold at sub-national level where finer variation in mobile money agent density and financial infrastructure is available, and whether longitudinal microdata can trace the household-level mechanisms through which active mobile money usage contributes to credit market deepening.

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