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Can Digital Financial Services Improve Household Coping Capacity?

Evidence from Nationally Representative Cross-Sectional Data in Kenya

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Notices

Abstract

Digital financial services (DFS) have expanded financial access in Kenya, but their contribution to household coping capacity may differ substantially across product types. This paper examines trends and socioeconomic correlates of DFS adoption and the associations between DFS use and household coping capacity using nationally representative FinAccess surveys from 2019, 2021, and 2024. The analysis combines descriptive statistics and pooled logistic regressions with inverse-probability-weighted-regression adjustment and propensity score matching. We distinguish between mobile banking savings, mobile money savings, mobile banking loans, mobile provider loans, and app-based digital credit. Mobile phone ownership, internet access, education, income, and financial decision-making are important correlates of adoption, though significant gender and regional disparities remain. Digital savings show the broadest and most consistent positive associations with household coping capacity. Mobile banking savings are associated with an increase of 14 percentage points in emergency saving, an increase of 7.5 percentage points in access to emergency funds, and reductions of 4 and 2.7 percentage points in food insecurity and difficulty accessing medical care, respectively. Mobile banking loans provide narrower benefits, mainly for financial planning and emergency liquidity. In contrast, app-based loans are associated with reduced emergency savings and financial endurance. The findings show that the welfare implications of DFS depend critically on product type. Savings-led digital finance can strengthen household preparedness, while short-term app-based credit may increase financial vulnerability.

Keywords: Digital innovation, financial inclusion, financial services, fintech.

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1. Introduction

An estimated 1.4 billion adults, primarily in sub-Saharan Africa and South Asia, remain outside the formal financial system, despite two decades of national financial inclusion strategies and donor investments aimed at closing this gap (Demirgüç-Kunt et al. 2022). Households in these regions mostly rely on informal financial mechanisms such as savings and credit groups and family remittances to manage everyday needs and cope with economic shocks (Karlan et al. 2016a). Barriers such as high transaction costs, limited financial literacy and awareness, and behavioral constraints often limit households' ability to access and effectively use formal financial services, especially among poor rural households (Karlan et al. 2016a). Limited access to finance then adversely affects households' welfare by reducing their ability to cope with unexpected shocks, which increases vulnerability and further perpetuates the poverty cycle (Dupas and Robinson 2013).

Digital financial services (DFS) have become an increasingly important way of overcoming these barriers and expanding financial inclusion through digital platforms. DFS encompasses digital credit, savings, and insurance accessed via mobile phones, agent networks, ATMs, and point-of-sale devices (Ozili 2018; Muthiora 2015). DFS has transformed financial inclusion by reducing delivery costs and extending services to remote and underserved populations beyond the reach of traditional financial institutions (Pazarbasioglu et al. 2020). In the context of this study, we define DFS as savings and credit that households access through digital channels. These include mobile-money platforms, mobile banking, and fintech lending applications, which are distinct from the same functions delivered through banks, cooperatives, savings groups, or informal arrangements.

Kenya is widely recognized as a global pioneer in DFS innovation and adoption. Flagship platforms such as M-Pesa have revolutionized access to financial services, enabling users to save, send, and receive money without needing a traditional bank account, while also providing micro-savings and digital credit options. As of 2020, global mobile money account holders exceeded 850 million: sub-Saharan Africa led adoption, with 21 percent of adults actively using mobile money services (Pazarbasioglu et al. 2020). In Kenya alone, more than 73 percent of adults are financially included, and of these, 98 percent use mobile money platforms (FSD 2017). Further, DFS offerings have rapidly evolved beyond person-to-person transfers to include digital insurance, merchant payments, salary disbursement, and government transfers, which are delivered by an increasingly diverse mix of banks, non-bank institutions, and fintech companies (Zetzsche et al. 2019).

Adoption and use of DFS have been shown to improve household welfare, particularly in developing countries where large segments of the population remain underserved by formal financial institutions (Tay, Tai, and Tan 2022). In Kenya, adoption of mobile money has been shown to increase household incomes by easing liquidity constraints, facilitating remittances, and promoting agricultural commercialization (Kikulwe et al. 2014). Additionally, mobile money adoption has been associated with increased agricultural income and market participation among rural households in Kenya (Kirui et al. 2013). Mobile money has also been found to strengthen informal risk-sharing networks and improve households' resilience to economic shocks (Jack and Suri 2014). In Uganda, DFS increased remittances, improved financial behavior, and enhanced household welfare outcomes (Munyegera and Matsumoto 2016; 2018).

Despite this rich evidence base, two important gaps remain. First, most existing evaluations treat DFS as a single, homogeneous intervention, commonly focusing on M-Pesa's person-to-person transfer function and disregarding substantial product-level heterogeneity in welfare effects (Suri 2017, Kirui et al. 2013). Comparative evidence examining digital savings, mobile banking, and digital credit within a unified empirical framework is scarce. The welfare implications of these products differ significantly and bundling them together for analysis can hide their differential effects (Johnen et al. 2021; Bharadwaj et al. 2019). Second, the role of consumer protection quality in mediating DFS outcomes has received limited systematic attention. Unexpected fees, service failures, opaque pricing, and aggressive debt collection practices are well-documented in Kenya's digital credit market (CGAP 2019; Kaffenberger et al. 2018), yet few studies formally account for these institutional factors when estimating DFS effects on household welfare and coping capacity. This omission may lead to overestimation of benefits and underestimation of the conditions in which DFS can harm financially vulnerable households.

This study addresses both gaps by using three waves of Kenya's nationally representative FinAccess surveys (FSD, 2019, 2021, 2024). We focus on three objectives. First, we characterize trends and disparities in DFS adoption across the study period and include products such as digital savings, mobile banking, and several forms of digital credit. Second, we identify the socioeconomic and contextual correlates of adoption using logistic regression with average marginal effects. Third, we estimate the association between use of each DFS product and multiple dimensions of household coping capacity, including food security, healthcare access, emergency savings, and financial planning, by using propensity score matching (PSM) and inverse-probability-weighted-regression adjustment (IPWRA). Findings can guide efforts to improve DFS delivery, highlight comparative advantages over traditional financial services, and provide scaling lessons for replicating successful models across Africa.

2. Literature Review

2.1 Financial market failures for households in sub-Saharan Africa

Households in sub-Saharan Africa face persistent barriers to formal financial services. This is mainly attributed to two well-documented market failures, adverse selection and moral hazard. These two key sources of financial market failure hamper credit delivery to these actors. Adverse selection arises when lenders cannot distinguish between high-risk and low-risk borrowers, leading to a need for predictive data models. Moral hazard, on the other hand, occurs when lenders are unable to observe borrowers' effort to repay loans or avoid losses, which may result in suboptimal loan use (Karlan et al. 2016b).

To address these issues, lenders have introduced credit bureaus, repayment reminders, and property-based enforcement mechanisms. For instance, Giné and colleagues (2012) show that biometric fingerprinting in Malawi led high-risk borrowers to self-select smaller loans and significantly improved repayment rates, from 44 percent among low-risk borrowers to 85 percent among high-risk ones. Similarly, Karlan and Zinman (2009) found that improved future access to loans incentivized current repayment behavior in South Africa. Field and colleagues (2013) observed that delaying loan repayment by two months allowed borrowers to invest more into businesses and double business formation, although they incurred higher default rates.

Digital innovation offers promising avenues to overcome these constraints. As digital credit products, such as M-Shwari in Kenya, gain traction, machine learning and digital scoring can replace traditional risk assessments, reduce adverse selection, and expand access at scale (Suri et al. 2016). Björkegren and Grissen (2020) demonstrate that data on call records from mobile phones can predict loan repayment with accuracy comparable to traditional credit scores, while Agarwalet al., and colleagues (2021) show that algorithmic credit scoring expands access to previously unserved borrowers in developing country markets. Still, information asymmetries also affect borrowers, with many lacking financial knowledge or misunderstanding product terms. A global review by Miller and colleagues (2014) found limited impacts of financial education programs on behavior change, underscoring the need for tailored, behaviorally informed product awareness and literacy efforts.

2.2 Access and use of digital financial services

Despite significant efforts to enhance financial inclusion over the past decade, approximately 1.4 billion adults worldwide remain unbanked, with the majority residing in sub-Saharan Africa and South Asia (Demirgüç-Kunt et al. 2022). Only 20 percent of adults in sub-Saharan Africa and South Asia report formal savings, compared to more than 50 percent in OECD countries. Constraints such as affordability, income volatility, physical distance from financial infrastructure, and documentation requirements are often cited as the main barriers to financial inclusion in these regions (Demirgüç-Kunt et al. 2022; Pazarbasioglu et al. 2020).

DFS offers a potential solution to these barriers to financial inclusion. Delivered through mobile phones, agent networks, and other remote channels, DFS products such as e-wallets, digital savings, and digital credit reduce transaction costs, eliminate the need for minimum balances, and extend reach to remote populations. In Rwanda, 31 percent of adults use DFS, primarily for remittances and income transfers, with fewer using it for savings or credit (FinScope Survey 2016). In Nigeria, DFS has improved financial inclusion and service delivery efficiency, particularly for low-income users (World Bank 2020).

Yet access is not evenly distributed. Evidence from Kenya's FinAccess surveys reveal persistent gaps in DFS adoption from income, geographic, and gender-based outcomes. While mobile money registration is near-universal in urban areas, active use of digital savings and credit products remains concentrated among higher-income, better-educated, and male-headed households (FSD Kenya 2024; Demirgüç-Kunt et al. 2022).

Another critical but often overlooked distinction is the difference between access and active use. Account registration, a widely used financial inclusion metric, substantially overstates functional inclusion, as high rates of account dormancy are well-documented across sub-Saharan Africa (Klapper et al., 2016). In Kenya, the gap between mobile money registration and active transacting has persisted across FinAccess survey waves, indicating that account ownership is necessary but not sufficient for financial inclusion. Mobile internet connectivity, which reached approximately 30 percent of adults in sub-Saharan Africa by 2023, continues to constrain uptake of mobile-internet-dependent DFS products in rural and lower-income segments (GSMA 2024). Gender also remains a structural barrier, as women in Kenya are less likely than men to own mobile phones, have internet access, and use digital credit products. Evidence suggests that these gaps reflect not only income differences but also social norms governing technology access and financial autonomy (Riley 2018; Bharadwaj et al. 2019). Data from the Financial Sector Deepening (FSD) Kenya (2017) also show that digital credit remains ill-suited to segments with irregular income, such as casual laborers and smallholder farmers. Reaching these groups requires deeper insights into their peculiar financial behaviors, irregular incomes, and needs.

2.3 Effects and benefits of digital financial services

DFS generates significant benefits across multiple dimensions, including transaction cost savings, enhanced risk-sharing, and economic empowerment. In Kenya, according to Jack and Suri (2014), M-PESA's reduction in transaction costs enabled users to access broader informal remittance networks, strengthening risk sharing and improving household coping capacity to negative income shocks relative to nonusers. Lower transaction costs enable broader risk-sharing networks. This is central to the ability of DFS to improve household coping capacity, and it motivates our focus on multiple coping capacity dimensions rather than income alone. Digital payments also facilitate more efficient social transfers. In India, Banerjee and colleagues (2016) reported that digitized wage transfers in a public works program reduced expenditure leakage by 38 percent and corruption by 25 percent.

In the agriculture sector, digitization can reinforce value chain relationships and transparency. For example, DFS have increasingly enabled businesses to conduct payments electronically rather than in cash, supporting improved recordkeeping and reducing the risks associated with handling cash, as reflected in greater use of digital merchant and person-to-business payment channels in Kenya's FinAccess 2024 data (Wairimu 2025).

Moreover, DFS promotes financial control and security. Text-based savings reminders increased savings rates by up to 16 percent in Bolivia and the Philippines (Karlan et al. 2011). By switching to mobile payments, farmers in Niger saved an amount of time equivalent to a week's worth of food (Aker et al. 2016). DFS also increases coping capacity for unseen shocks: M-Pesa users were better able to cope with income shocks and access emergency funds (Suri and Jack 2016).

Emerging evidence shows that DFS can also reduce poverty. Suri and Jack (2016) found that M-Pesa helped lift 2 percent of Kenyan households out of poverty. Similarly, smallholder cocoa farmers in Côte d'Ivoire who received digital payments increased their savings and improved food security (Lonie et al. 2018). In Uganda, a randomized controlled trial found that DFS improved livelihood outcomes, such as reducing the likelihood of needing to skip meals and increasing self-employment (Wieser and Bruhn 2018).

On a macro level, DFS adoption can boost GDP by up to 2 percent, reduce government transfer costs, and enable delivery of services such as clean water and solar energy through digital pay-as-you-go systems (Pazarbasioglu et al. 2020). The DFS ecosystem also creates jobs: as of 2016, more than 1.5 million DFS agents operated in sub-Saharan Africa, generating $400 million in annual commissions (GSMA 2016).

Remittances sent via DFS are also critical during crises. During COVID-19, the decline in remittance flows threatened household consumption, education, and healthcare, highlighting the importance of low-cost, digital remittance platforms to sustain livelihoods and local economies (IFAD 2020).

The literature establishes that DFS can meaningfully improve household welfare and coping strategies, but it also reveals important research gaps. Most evaluations focus on a single product (most commonly M-Pesa's person-to-person transfer function) and measure a narrow set of outcomes over short time horizons. Product-level heterogeneity between savings, credit, and insurance products has received limited attention within unified empirical frameworks, despite growing evidence that digital credit carries risks of over-indebtedness and financial stress (Johnen et al. 2021; Suri, Bharadwaj et al. 2021) and increasing focus on bundling by governments and private players.

3. Methodology

3.1 Trends and disparities in use of digital financial services

The analysis begins with descriptive statistics and trend analysis to assess changes in DFS uptake and usage over time and across demographic subgroups. Cross-tabulations by year are used to assess temporal and spatial patterns in DFS adoption.

3.2 Correlates of digital financial services usage

The correlates of DFS adoption are analyzed using repeated cross-sectional household survey data for the years 2019, 2021, and 2024, which are complemented by a pooled dataset combining all survey rounds. The analysis focuses on multiple binary indicators of DFS usage, including savings through mobile banking, savings through mobile money, mobile banking loans, loans from mobile providers, and digital loans. These indicators capture different dimensions of digital financial inclusion relevant to the FinAccess dataset. Observations with missing values in key covariates such as marital status, education level, and internet access are excluded to ensure consistent model estimation across survey waves.

The empirical analysis employs a binary logistic regression model to estimate the probability of DFS adoption as a function of demographic, socioeconomic, digital access, and financial vulnerability characteristics. For each DFS outcome Y_i, the probability of adoption is modeled as a logistic function of explanatory variables X_i, allowing estimation of the marginal contribution of each covariate to DFS uptake. Separate models are estimated for each survey year to capture temporal variation in DFS adoption dynamics, while pooled models are used to identify structural determinants common across the three survey rounds. This approach is consistent with empirical strategies commonly applied in studies on financial inclusion and in broader development economics research on digital finance adoption (Gakpa 2023; Demirgüç-Kunt et al. 2022).

The logistic regression is appropriate for modeling a dichotomous outcome, where the dependent variable $\boldsymbol{D_i}$ takes a value of 1 if a household adopts DFS and 0 otherwise. The model estimates the probability of adoption as a function of household-level, individual, and regional characteristics, accounting for the nonlinear relationship between covariates and the probability of DFS usage (Hosmer, Lemeshow, and Sturdivant 2013).

Let D_i denote the binary outcome variable representing DFS adoption for household i, and let X_i be a vector of explanatory variables, including household income, education level, gender of household head, digital literacy, asset endowment, income, and other covariates. The logistic regression model is expressed as

$$logit[P(D_i = 1|X_i)] = \ln\left(\frac{P(D_i = 1|X_i)}{1-P(D_i = 1|X_i)}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}, \quad (1)$$

where $P(D_i = 1|X_i)$ is the probability that household i adopts DFS, given covariates X_i, β_0 is the intercept term, and $\beta_i, \ldots . \beta_k$ are the coefficients corresponding to each covariate $X_{1i}, \ldots . X_{ki}$.

The logit transformation ensures that predicted probabilities are bounded between 0 and 1. Maximum likelihood estimation is used to estimate the model parameters $\boldsymbol{\beta}$, providing consistent and efficient estimates for binary outcomes (Greene 2018).

The model fit is assessed using standard diagnostic measures, including the Hosmer-Lemeshow goodness-of-fit test and the area under curve (Hosmer Lemeshow, and Sturdivant 2013). Multicollinearity among explanatory variables is evaluated using variance inflation factors, and robust standard errors are employed to account for potential heteroskedasticity.

This logistic regression framework allows for systematic identification of the key correlates of DFS adoption, providing insight into how household socioeconomic characteristics, education, age, household size, asset index, and geographic context shape the likelihood of using DFS. Understanding these correlates is essential for informing policy interventions aimed at promoting financial inclusion and expanding the reach of DFS in diverse populations.

3.3 Effect of digital financial services usage and household coping capacity

This study uses PSM and IPWRA to estimate the association between DFS use and household coping capacity, under the assumption that adoption of DFS is driven by observable household characteristics. These quasi-experimental methods are appropriate for the FinAccess longitudinal data, as DFS usage is not randomly assigned. In this regard, households may self-select into DFS usage based on observable characteristics such as income, education, access to technology, and prior financial experience, factors which are also likely to influence household coping capacity outcomes. PSM reduces selection bias by matching treated and control/comparison households with similar covariates, while IPW reweighs all observations to create a pseudo-population in which covariates are independent of treatment status, retaining efficiency and comparability. In addition, the study employs the doubly robust IPWRA method, which combines IPW with outcome regressions to improve robustness. This ensures that the estimated average treatment effect on the treated (ATET) remains consistent, even if the treatment or outcome regression model is mis-specified (Imbens and Wooldridge 2009). Using these complementary approaches enhances confidence in the estimated causal effects of DFS usage on household coping capacity.

3.3.1 Propensity-score-matching estimation

Under the PSM approach, selection bias from nonrandom assignment for use or non-use of DFS is reduced by matching households with similar observable characteristics. Introduced by Rosenbaum and Rubin (1983), PSM estimates the probability that a household is assigned to a DFS based on these observed characteristics. Households that are assigned to DFS are then matched with one or more households that are not assigned but have similar propensity scores. This approach creates comparison groups that are similar in observed characteristics, allowing for a more reliable estimate of the causal effect of DFS usage on coping capacity outcomes. The ATET is calculated as the average difference in coping capacity outcomes between these matched households from treatment and comparison groups.

Let Y_i denote the outcome of interest (household coping capacity), D_i a binary treatment indicator ($D_i = 1$ if the household uses DFS; $D_i = 0$, if otherwise), and X_ia vector of observed covariates that influence treatment assignment. The propensity score, defined as the conditional probability of receiving treatment, is estimated using a logit model to ensure appropriate balancing of covariates between treated and control groups. The propensity scores to be estimated is expressed as

$$e(X_i) = P(D_i = 1|X_i). \tag{2}$$

The ATET captures the causal effect of the treatment (DFS usage) on household coping capacity (Imbens and Wooldridge 2009). It is formally expressed as

$$ATET = E(Y_{1i} - Y_{0i}|D_i = 1), \tag{3}$$

where Y_{1i} is the outcome for the ith household if it is treated (using DFS), Y_{0i} is the outcome for the ith household if it is not treated (not using DFS), and Di is a binary indicator of treatment status (1 = using DFS, 0 = not using DFS) (Heckman, Ichimura, and Todd, 1997). The ATET is also referred to as the conditional mean impact, representing the association of the treatment among households that received it. It denotes the difference between the observed outcome under treatment and the unobserved counterfactual outcome had they not been treated. A simple comparison of the mean outcomes between treated and control units is given by

$$E(Y_1|D_i = 1) - E(Y_0|D_i = 1) = ATT + \varepsilon, \tag{4}$$

where ε is the selection bias, which is also defined as

$$\varepsilon = E(Y_0|D_i = 1) - E(Y_0|D_i = 0). \tag{5}$$

This bias occurs because the potential outcome of the treated group if they had not received the treatment (Y0 | D_i=1) may differ from the observed outcome of the control/comparison group (Y0 | D_i=0) (Rosenbaum and Rubin 1983). Therefore, the true ATT can only be identified if, in the absence of treatment, the expected outcomes of the treatment and control units are the same

$$E(Y_0|D_i = 1) = E(Y_0|D_i = 0). \tag{6}$$

This condition ensures that any observed difference in outcomes between the treated and control groups can be attributed solely to the treatment itself (Imbens and Wooldridge 2009; Heckman et al. 1997).

3.3.2 Inverse probability weighting for average treatment effect on the treated estimation

In addition to the PSM approach, this study employs inverse probability weighting (IPW) to estimate the impact of DFS usage on household coping capacity outcomes. The IPW approach reweighs observations to account for the nonrandom assignment of treatment, generating a pseudo-population in which the distribution of observed covariates is independent of treatment status (Hirano, Imbens, and Ridder 2003; Imbens and Wooldridge 2009). Unlike PSM, IPW retains all observations, improving statistical efficiency while maintaining comparability between treated and control/comparison groups. X_i and the propensity score, previously defined in Section 3.3.1, are used to construct the IPW weights that balance the treated and control/comparison groups.

The IPW estimator for the ATET is written as

$$ATET_{IPW} = \frac{1}{N_1}\sum_{i:D_i=1} Y_i - \frac{1}{N_1}\sum_{i:D_i=0} \frac{e(X_i)}{1-e(X_i)} Y_i, \qquad (7)$$

where $N_1 = \sum_{i=1}^{N} D_i$ represents the number of treated households (using DFS). This formulation weights control/comparison households according to the odds of treatment, creating a control/comparison group comparable to the treated group in terms of observed covariates. As in the PSM approach, the difference between the reweighted control/comparison outcomes and the counterfactual outcome for treated units captures potential selection bias, which can be written as

$$\varepsilon_{IPW} = E(Y_{0i}|D_i = 1) - \frac{1}{N_1}\sum_{i:D_i=0} \frac{e(X_i)}{1-e(X_i)} Y_i. \qquad (8)$$

When the conditional independence assumption holds and propensity scores are correctly specified, the selection bias (ε_{IPW}) approaches 0 (Rosenbaum and Rubin 1983; Imbens and Wooldridge 2009). The IPW approach relies on three key assumptions, namely, that treatment assignment is independent of potential outcomes given observed covariates X_i, every unit has a nonzero probability of receiving treatment ($0 < e(X_i) < 1$), and the model estimating the propensity scores ($e(X_i)$ accurately reflects the relationship between covariates and treatment assignment (Hernán and Robins 2020). Under these conditions, the IPW estimator provides a robust estimate of the ATET, representing the average causal effect of DFS usage among households that use DFS. By using all available observations and appropriately weighting controls/comparisons, IPW complements the PSM estimates and enhances the reliability of causal inference (Imbens and Wooldridge 2009; Hernán and Robins 2020).

3.3.3 Doubly robust estimation using inverse-probability-weighting-regression adjustment

To further strengthen our causal inference, this study employs the doubly robust IPWRA approach, which combines inverse-probability weighting with regression adjustment of the outcome model. Unlike standard IPW, IPWRA provides consistent ATET estimates even if the treatment model or the outcome model is mis-specified (Imbens and Wooldridge 2009). The doubly robust estimator of ATET can be written as

$$ATET_{DR} = \frac{1}{N_1}\sum_{i:D_i=1}(Y_i - Y_0(X_i)) + \frac{1}{N_1}\sum_{i:D_i=0}\frac{e(X_i)}{1-e(X_i)}(Y_i - Y_0(X_i)), \quad (9)$$

where $N_1 = \sum_{i=1}^{N} D_i$ represents the number of treated households (using DFS), Y_i is the observed outcome, $e(X_i) = P(D_i = 1|X_i)$ is the propensity score, and $Y_0(X_i]$ is the predicted counterfactual outcome for treated units if they had not received treatment, obtained from the outcome regression model.

The first part of the doubly robust equation represents the deviation of treated households' observed outcomes from their predicted counterfactual outcomes, capturing the effect of DFS usage among households that received treatment. The second term reweighs control/comparison households' outcomes according to the odds of treatment, creating a pseudo-population that is comparable to the treated group in terms of observed covariates. Together, these two components produce a consistent estimate of the ATET, which remains unbiased if either the treatment assignment model or the outcome regression model is correctly specified, reflecting the doubly robust property of the estimator.

The selection bias under the doubly robust estimation can be written as

$$\varepsilon_{DR} = E(Y_{0i}|D_i = 1) - \frac{1}{N_1}\sum_{i:D_i=0}\frac{e(X_i)}{1-e(X_i)}(Y_i - Y_0(X_i)) - \frac{1}{N_1}\sum_{i:D_i=1}Y_0(X_i)). \quad (10)$$

In the selection bias expression, the first term represents the population counterfactual mean for treated units, the second term captures the weighted difference between control outcomes and their predicted counterfactuals, and the third term is the mean predicted counterfactual outcome for treated units. This selection bias approaches 0 if either the treatment or the outcome regression model is correctly specified, reflecting the doubly robust property.

The doubly robust approach follows three key steps:

1. Treatment model: Logit regression is used to estimate the probability of a household using DFS (the propensity score), as defined in Section 3.3.1.
2. Outcome model: Using the inverse-probability weights derived from the treatment model, a weighted logit regression is fitted to predict household coping capacity outcomes for treated and untreated households.

3. ATET estimation: The means of the predicted outcomes are then used to calculate the ATET, capturing the causal effect of DFS usage on household coping capacity.

These three steps of the doubly robust method are jointly estimated using the *teffects ipwra* command in the Stata statistical software package. In this instance, the doubly robust method is superior to other commonly used selection-on-observable estimators, such as PSM. This is because the doubly robust property ensures that even if either one of the treatment or outcome models is mis-specified, the ATET estimates will still be consistent (Imbens and Wooldridge 2009).

The conditional independence assumption requires that conditional on observed covariates, DFS adoption is unrelated to potential coping capacity outcomes. We argue that this assumption is plausible in our setting for two reasons. First, the FinAccess survey is rich in the characteristics most likely to jointly determine both DFS adoption and household coping capacity: income, education, employment type, digital access, geographic location, prior loan default history, and household financial goals. These are precisely the factors identified in the DFS adoption literature as the primary correlates of selection into DFS (Pazarbasioglu et al. 2020; Karlan et al. 2016b). Second, by estimating the ATET rather than theaverage treatment effect (ATE), we restrict inference to households that use DFS, further narrowing the comparison to nonusers who resemble them on observable characteristics. We nonetheless acknowledge that unobserved factors such as risk preferences, intrinsic motivation to save, or trust in financial institutions may not be fully captured by our covariate set and could introduce residual bias. Estimates should therefore be interpreted as the effect of DFS usage among observationally similar households, rather than as unconditional causal effects.

3.4 Definition of household coping capacity (outcome) variables

Household coping capacity was assessed using six outcome variables that capture households' ability to meet basic needs, manage financial shocks, and maintain financial stability:

- Food insecurity: This variable assesses whether a household experiences periods without sufficient food to eat. This indicator proxies the household's ability to consistently meet basic nutritional needs.
- Healthcare access: This variable assesses whether household members had to forego medical care or medicine whenever needed. It proxies a household's ability to meet healthcare needs without experiencing financial hardship.
- Coping with unexpected expenses: This variable assesses a household's ability to cover unforeseen costs without severe financial disruption. It reflects short-term financial flexibility in responding to shocks.
- Goal-oriented saving: This variable assesses whether the household sets aside money toward a specific financial objective (such as education, investment, or asset

acquisition). This variable reflects forward-looking financial planning and disciplined saving behavior.

- Emergency-fund access: This variable assesses a household's ability to quickly mobilize funds in response to an unexpected shock, either from savings or other reliable financial sources. This indicator captures liquidity and immediate financial coping capacity.
- Financial endurance: This variable assesses a household's ability to make available income or resources last between income receipt periods, reflecting day-to-day financial management and stability in meeting regular expenses.
- Saving for emergencies: This variable assesses whether a household regularly sets aside money to deal with unforeseen events such as illness, job loss, or urgent repairs. This variable reflects precautionary saving behavior and the household's preparedness for financial shocks.
- Financial planning: This variable assesses whether a household engages in proactive, forward-looking management of its financial resources, such as budgeting, setting financial goals, or planning for future expenses. This variable captures the extent to which households intentionally organize and manage their finances to achieve stability and long-term objectives.

3.5 Definition of digital financial services

This study examines the socioeconomic correlates of adopting five DFS and their association with household coping capacity. These digital financial products include:

- Mobile banking savings, which are held in a bank account accessed via a mobile banking app or platform, such as Equitel, KCB Mobile Banking App, and M-Co-op Cash
- Mobile money savings, which are stored in a mobile money wallet, typically outside traditional banks, and use telecom-operated platforms (such as M-Shwari or KCB M-Pesa, Airtel Money Lock Savings Account, and T-Kash PesaLink Savings)
- Mobile banking loans, which are issued and managed through a mobile banking platform linked to a formal bank account, such as NCBA Loop, Equitel Eazzy Loan, KCB Mobile Loans, and Absa Timiza
- Mobile money loans, which are accessed via mobile money platforms, often short-term and unsecured, are not necessarily linked to a bank account, such as Fuliza, and KCB M-PESA
- Digital credit apps on smartphones that offer instant credit, often using alternative data to assess creditworthiness, such as Branch, Tala, and Okash, Stawika, Zenka, Kashway, and iPesa

3.6 Data and sampling framework

The data used in this study are drawn from the FinAccess Household Surveys for Kenya, conducted in 2019, 2021, and 2024. The FinAccess surveys are a series of nationally representative, cross-sectional household surveys implemented by the Kenya National Bureau of Statistics in collaboration with the Central Bank of Kenya and Financial Sector Deepening (FSD) Kenya, with additional support from financial sector regulators and development partners. These surveys are designed to monitor developments in financial inclusion by capturing demand-side information on access to, use of, and impact of a wide range of financial services and products, including DFS such as mobile money, mobile banking, and other digitally delivered financial services and products. Each wave of the FinAccess survey employs a multi-stage stratified cluster sampling design based on the Kenya Household Master Sample Frame, which is derived from the national census frame. Households are selected systematically within enumeration areas to ensure representativeness at the national, urban, and rural levels, as well as across Kenya's 47 counties. Data are collected through face-to-face interviews with individuals ages 16 and older, and sample weights are applied to adjust for selection probabilities and nonresponse, ensuring that estimates reflect the adult Kenyan population.

The 2019 FinAccess Household Survey captures a period of rapid evolution in Kenya's financial services landscape by extending measurement of financial inclusion beyond basic access to include dimensions of usage, quality, and impact. The 2021 survey updates these measures at a time of heightened digital adoption and economic change, including measurement of financial coping capacity and health amid the COVID-19 pandemic and expanded county coverage. The 2024 survey further refines the measurement framework to reflect emerging financial innovations and consumer behavior, with enhanced modules on DFS usage, financial health, and related outcomes. Together, the 2019 (n= 10,970), 2021 (n= 22,024), and 2024 (n=20,871) FinAccess datasets provide rich, comparable data that support examination of trends in DFS adoption and the causal effects of DFS usage, defined in this study as using at least one digital financial product, on a range of household coping capacity outcomes across Kenya.

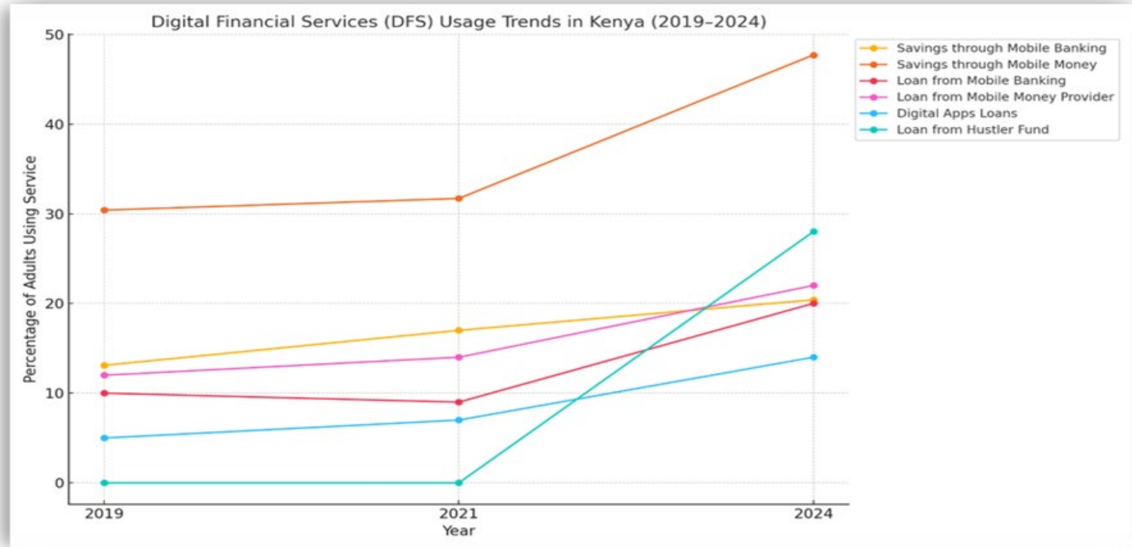
4. Results and discussions

4.1 Trends and disparities in use of digital financial services

Kenya's DFS landscape expanded substantially between 2019 and 2024, though this aggregate growth masks important heterogeneity across products and population groups. Mobile money registration rose from 72.88 percent in 2019 to 77.8 percent in 2024, consolidating its position as the dominant entry point into digital finance (Figure 1). Mobile banking registration followed a more uneven trajectory, dipping slightly in 2021 before recovering to 24.67 percent by 2024, suggesting growing but fragile engagement with bank-linked digital platforms. Beyond these registration trends, a persistent gap between account ownership and active use is evident. Savings through mobile money providers peaked sharply in 2021, likely reflecting heightened reliance on digital platforms during the COVID-19 pandemic, before declining to 29.88 percent in 2024 (well below the 2019 level of 40.47 percent). Savings through mobile banking also stagnated, averaging around 12 percent across all three waves. These patterns indicate that expanded registration has not translated proportionally into sustained active use, particularly for digital savings products.

Digital credit trends are equally uneven. Mobile banking loans remained broadly stable at around 7–8 percent across waves, while loans from mobile providers grew modestly from 15.72 percent in 2021 to 16.42 percent in 2024 (Table 1). Digital app loans declined sharply, from 6.46 percent in 2019 to below 2 percent in subsequent waves, a pattern consistent with evidence on the deterrent effects of high interest rates, hidden fees, and aggressive enforcement practices on borrower reengagement (Johnen et al. 2021).

Figure 1: Trends in adoption of digital financial services



Source: Authors’ compilation from FinAccess 2019, 2021,2024 data

Disparities in adoption remain pronounced. Across all three waves, adoption is consistently higher among younger, more educated, urban, and higher-income households (Table 1). Gender gaps persist, particularly for mobile banking savings and digital credit, with male respondents more likely to adopt across most products and years. Digital savings products exhibit the smallest adoption gaps across socioeconomic groups, suggesting lower barriers to entry relative to credit products, which typically require stronger digital literacy, creditworthiness signals, or repayment capacity. These patterns are consistent with diffusion-of-innovation theory, in which early adoption is concentrated among more advantaged groups before gradually broadening as ecosystems mature.

Table 1: Digital financial services used

Dependent Variables	2019	2021	2024	Pooled
Registered on mobile money	72.88	75.33	77.80	75.92
Registered on mobile banking	19.47	17.79	24.67	20.86
Savings through mobile banking platform	13.40	11.70	12.59	12.34
Savings/keeping through mobile money provider	40.47	51.26	29.88	40.79
Loan from mobile banking	7.41	8.03	7.69	7.79
Loan from mobile provider (such as Fuliza loan, Equity's Boostika)	-	15.72	16.42	16.06
Digital app loans	6.46	1.67	1.77	2.51

Source: Authors' compilation from FinAccess 2019, 2021,2024 data.

4.2 Correlates of digital financial services adoption

Table 2 reports average marginal effects from pooled logistic regressions for five DFS products. The estimates identify characteristics associated with adoption after controlling for demographic, socioeconomic, livelihood, digital-access, and regional factors. They should therefore be interpreted as conditional associations rather than causal effects. Four broad patterns emerge: digital access is the strongest correlate of adoption; income, assets, and education remain important; household agency and livelihood characteristics shape participation; and substantial geographic gaps persist for several products.

4.2.1 Digital access is the strongest correlate of DFS adoption

Mobile phone ownership has the largest marginal effect in every model, although its importance varies markedly by product. Holding other characteristics constant, phone ownership is associated with a 48-percentage-point increase in the probability of saving through a mobile money provider, a 23.6-percentage-point increase in borrowing from a mobile provider, and a 22-percentage-point increase in mobile banking savings. The corresponding association is smaller for mobile banking loans (10.8 percentage points) and especially app-based loans (1.8 percentage points). Internet access is also positive and statistically significant across all products, increasing adoption probabilities by approximately 1.7–5.9 percentage points. These results indicate that basic connectivity remains a prerequisite for DFS participation, but also show that product design matters: mobile money products depend primarily on handset access, whereas bank-linked and app-based products additionally require connectivity, digital capability, and access to more formal financial infrastructure. The digital divide therefore continues to translate directly into unequal access to digital finance.

4.2.2 Socioeconomic resources and education remain important

Income is positively associated with adoption of all five products, with the largest marginal effects for mobile banking savings and mobile money savings. Household assets show a similarly positive relationship with both savings products and mobile banking loans, but are negatively associated with mobile provider loans and unrelated to app-based lending. This contrast suggests segmentation within the DFS market: relatively better-resourced households are more likely to use savings and formal bank-linked products, while mobile provider credit reaches a somewhat different and potentially more financially constrained clientele. Housing quality reinforces this pattern, as respondents living in temporary or traditional dwellings are substantially less likely to adopt most bank-linked and provider-based products than those living in permanent structures. Education displays a strong and monotonic gradient. Relative to respondents with no formal education, primary education raises adoption probabilities by 4.5–9.4 percentage points for the four main savings and credit products, while postsecondary education raises them by 7.3–12.7 percentage points. The education gradient is much smaller for app-based loans, although it remains positive. Education may facilitate adoption by improving financial literacy, confidence in using digital interfaces, and the ability to assess product terms and risks. Expanding access alone may therefore be insufficient without complementary investments in financial and digital capability.

4.2.3 Gender, household agency, livelihoods, and prior financial experience also matter

Men are more likely than women to adopt mobile banking savings, mobile money savings, mobile banking loans, and mobile provider loans, with the largest gender gap observed for provider-based credit (3.6 percentage points). No statistically significant gender difference is evident for app-based loans. Although these pooled gaps are modest relative to the effects of phone ownership and education, their persistence after controlling for income, assets, and digital access indicates that women may face additional constraints, including weaker control over resources, lower confidence in formal financial institutions, or product designs that do not adequately reflect their financial needs. Consistent with this interpretation, respondents whose spouse or another household member makes financial decisions are generally less likely to adopt DFS than respondents who make decisions themselves, whereas joint decision-making is mostly not statistically different from individual decision-making. This points to personal financial agency, rather than household structure alone, as an important correlate of adoption. Livelihoods further differentiate DFS use. Relative to salaried employees, self-employed respondents are more likely to use mobile banking savings, mobile money savings, mobile banking loans, and app-based loans. Farmers are substantially more likely to save through mobile money but slightly less likely to use mobile banking loans, while casual and seasonal workers are less likely to adopt bank-linked savings and credit products. These patterns are consistent with the role of DFS in managing irregular business and farm cash flows, but also show that unstable earnings can restrict access to products that rely on formal eligibility requirements or regular repayment capacity. Prior loan default is positively associated with every product and especially with mobile banking and mobile provider loans. This should not be interpreted as evidence that default promotes adoption; more plausibly, it captures previous exposure to digital borrowing, repeated credit demand, or financial distress that leads households to continue seeking liquidity across multiple channels.

Table 2: Logistic regression results for correlates of digital financial services adoption

Variables	Mobile banking savings	Mobile money savings	Mobile banking loans	Mobile loan provider	Digital loan application
Age	-0.00165***	-0.00104***	0.000309**	-0.00250***	-0.000379***
Log income	0.0156***	0.0122***	0.00546***	0.0104***	0.00347***
Type dwelling unit: Permanent building					
Semi-permanent	-0.0182***	-0.0210***	-0.0139***	-0.00180	-0.00204
Temporary	-0.0389***	-0.0297**	-0.0280***	-0.0340***	-0.00124
Traditional	-0.0587***	-0.0254	-0.0582***	-0.0472***	-0.00865
Asset index 0–100	0.000989***	0.00178***	0.000900***	-0.000826**	0
Total TLU	-0.000318	-0.000701	-0.000605	-0.000576	-0.000418
Household size	-0.00221*	-0.00422***	-0.00127	0.000778	-0.000782
Rural	0.00448	-0.00232	-0.00606	-0.0165***	-0.00758***
Male	0.0127***	0.0223***	0.0116***	0.0359***	0.00203
Education: None					
Primary	0.0718***	0.0596***	0.0452***	0.0939***	0.00789***
Secondary	0.104***	0.0659***	0.0735***	0.116***	0.0163***
Postsecondary	0.126***	0.0730***	0.0827***	0.127***	0.0280***
Goal: Putting food on the table					
Educating yourself or your family	0.0168***	0.0166**	0.000873	-0.00391	-0.00329
Starting/improving your business/farm/livestock	0.0216***	0.00245	0.00641	0.0120	-0.00176
Health (yours or family/others)	-0.0125	-0.0375***	-0.000612	-0.0119	-0.000110
Other goals	0.0231***	0.0321***	0.0128**	0.0242***	-0.000308
Decision-maker: Self					
Spouse	-0.0201***	-0.0293***	-0.0264***	-0.0250***	-0.00273
Jointly (with spouse)	0.00893	-0.00781	0.00259	-0.00442	-0.00146
Others	-0.0161**	-0.0794***	-0.0303***	-0.0361***	0.000683

Source of income: Employee					
Farming (crops, keeping livestock, fishing, aquaculture)	-0.0124	0.0712***	-0.0143**	-0.00772	-0.00213
Casual worker/seasonal worker	-0.0199***	-0.00594	-0.0167***	0.00206	0.00127
Running own business/self-employed	0.0273***	0.0666***	0.0136**	0.00401	0.00519*
Others	-0.0319***	-0.0304**	-0.0181***	-0.0186**	0.00162
mobile	0.220***	0.480***	0.108***	0.236***	0.0183*
Internet access	0.0586***	0.0307***	0.0343***	0.0423***	0.0172***
Defaulted on previous loan	0.0556***	0.0559***	0.123***	0.176***	0.0334***
Receive financial assistance	-0.00301	-0.0377***	0.00975**	-0.0111**	-0.00117
Lack school fees	-0.0132***	-0.0140**	0.00980**	0.00194	-0.00140
Improved financial status	0.00353	0.0151	-0.0104*	-0.00525	-0.00374
Region: Nairobi					
Coast	-0.0475***	-0.0809***	-0.0170	-0.0559***	-0.00518
Northeastern	-0.131***	-0.168***	-0.0960***	-0.194***	-0.0213***
Eastern	-0.0776***	-0.0981***	-0.0363***	-0.0721***	-0.00296
Central	-0.0597***	-0.00159	-0.00252	-0.0518***	-0.000204
Rift Valley	-0.0476***	-0.0606***	-0.0261**	-0.0429***	-0.00541
Western	0.0359**	0.00156	0.0183	-0.0180	-0.000943
Nyanza	-0.0167	-0.0335	-0.0162	-0.0633***	-0.00714
Observations	22,174	22,174	22,174	22,174	22,174
Standard errors in parentheses					

Note: Significance levels; *** 1%, ** 5%, * 10%

Source: Authors' compilation from FinAccess 2019, 2021,2024 data.

4.2.4 Geographic disparities are declining

Geographic inequalities remain substantial despite the national reach of DFS. Compared with Nairobi, residents of most regions are less likely to adopt mobile banking savings, mobile money savings, and mobile provider loans after other observed characteristics are held constant. The largest gaps occur in the northeastern region, where adoption probabilities are lower by 13.1 percentage points for mobile banking savings, 16.8 percentage points for mobile money savings, 9.6 percentage points for mobile banking loans, and 19.4 percentage points for mobile provider loans. Rural residence is additionally associated with lower use of mobile provider and app-based loans, although it is not significant for the two savings products or mobile banking loans after controlling for region and other covariates. Western Kenya is the only region with a positive association for mobile banking savings relative to Nairobi.

These results suggest that the diffusion of digital finance has not eliminated spatial exclusion: connectivity, agent density, market access, and formal banking infrastructure likely continue to determine which products are practically accessible. Taken together, the findings imply that policies to expand DFS adoption should combine investments in mobile and internet access with financial capability, gender-responsive product design, stronger consumer protection, and geographically targeted delivery. The marked differences across products also caution against treating DFS adoption as a single outcome, since the factors associated with savings are not identical to those associated with reliance on short-term digital credit.

Two additional patterns are notable. First, respondents who had previously defaulted on a loan were significantly more likely to adopt all five DFS products. Relative to those without a previous default, their probability of using mobile banking savings and mobile money savings was higher by 5.6 percentage points in each case. The association was substantially larger for credit products: 12.3 percentage points for mobile banking loans, 17.6 percentage points for mobile provider loans, and 3.3 percentage points for app-based digital loans. This pattern may reflect greater familiarity with borrowing and continued reliance on digital credit among financially constrained users, although it also raises concerns about repeat borrowing and debt vulnerability.

Second, relative to formally employed respondents, self-employed individuals were 2.7 percentage points more likely to use mobile banking savings, 6.7 percentage points more likely to use mobile money savings, and 1.4 percentage points more likely to use mobile banking loans. They were also 0.5 percentage points more likely to use app-based loans, although the association was only weakly significant, while the estimate for mobile provider loans was small and statistically insignificant. By contrast, casual and seasonal workers were 2 percentage points less likely to use mobile banking savings and 1.7 percentage points less likely to use mobile banking loans. These findings suggest that entrepreneurial activity increases demand for flexible digital saving and financing tools, while irregular and unstable earnings may limit engagement with more formal DFS products.

4.3 Effects of digital financial services use on household coping capacity

The estimates report adjusted differences in household coping capacity outcomes between users and nonusers of each DFS product. IPWRA is the primary estimator, while nearest-neighbor matching and kernel PSM provide robustness checks. The main text focuses on pooled estimates in Tables 3 and 4; year-specific estimates for 2019, 2021, and 2024 are reported in Annex Tables B1–B7.

The pooled results show marked differences across DFS products. Digital savings are associated with the broadest and most consistent improvements in coping capacity. Mobile banking loans improve selected liquidity and financial-management outcomes, while mobile provider loans yield narrower gains. App-based digital loans show limited positive effects and are associated with weaker emergency saving and financial endurance. The similarity of many IPWRA and PSM estimates strengthens confidence in these overall patterns, although differences across survey waves remain important and are documented in the Annex.

4.3.1 Digital savings: Consistent positive effects across all coping capacity outcomes

Digital savings show the most comprehensive and internally consistent positive associations across the seven coping outcomes. In the pooled IPWRA estimates (Table 3), mobile banking savings reduce the probability of going without sufficient food by 4 percentage points and of foregoing needed medical care by 2.7 percentage points. Mobile money savings yield corresponding reductions of 1.9 and 3.3 percentage points. The PSM estimates in Table 4 are similar in sign and generally close in magnitude, suggesting that these findings are not driven by the choice of estimator. The results are consistent with evidence that digital savings and mobile money can lower transaction costs, facilitate transfers, and improve access to liquid resources during adverse income or expenditure shocks (Apeti 2023; Diallo 2025).

The largest gains arise in precautionary and forward-looking financial behavior. Mobile banking savings increase the likelihood of saving for emergencies by 14 percentage points, financial planning by 7.1 percentage points, goal-oriented saving by 8 percentage points, and access to emergency funds by 7.5 percentage points. Mobile money savings increase the same outcomes by 10.4, 9.3, 4.4, and 4.2 percentage points, respectively. These are sizeable effects relative to the food- and health-related outcomes and indicate that the principal contribution of digital savings may lie not only in smoothing consumption after shocks, but also in strengthening households' ex ante preparation for them.

This pattern has an important behavioral interpretation. Digital savings platforms may create a degree of commitment, separation, and visibility that makes it easier for households to protect funds from routine expenditure and to save toward a defined purpose. The strong financial-planning effects are consistent with earlier evidence that commitment mechanisms and digital reminders can alter saving behavior and improve financial discipline (Karlan et al. 2011). Because the comparison group includes many households using conventional saving instruments, the estimated associations should not be read simply as digital users versus financially inactive households. Rather, they suggest that the digital form of saving may provide additional convenience, liquidity, or behavioral structure beyond that available through some traditional channels.

Financial endurance is the main point of differentiation between the two savings products. Mobile banking savings improve households' ability to make money last by 2.8 percentage points under IPWRA and by 2.8–3.1 percentage points under PSM. By contrast, the pooled estimate for mobile money savings is small and statistically insignificant. One possible explanation is that bank-linked savings products are more likely to hold balances intended for medium-term financial management, whereas mobile money accounts may be used more intensively for transactions and short-term transfers. Overall, however, the pooled evidence indicates that digital savings strengthen both immediate shock absorption and longer-term financial preparedness. The year-specific results in Annex Tables B1–B7 provide a more detailed view of how the magnitude and significance of these relationships changed between 2019, 2021, and 2024.

4.3.2 Mobile banking loans: Modest and context-dependent effects

Mobile banking loans display positive but more selective associations than digital savings. In the pooled IPWRA estimates, they increase saving for emergencies by 3.7 percentage points, financial planning by 5.1 percentage points, goal-oriented saving by 2.5 percentage points, and access to emergency funds by 4.3 percentage points. The PSM estimates confirm the gains in financial planning and emergency-fund access, while support for emergency and goal-oriented saving is weaker across matching algorithms. The strongest and most robust result is therefore not asset accumulation, but the ability to mobilize resources and organize finances when needs arise.

This narrower pattern is consistent with the economic function of formal credit. A mobile banking loan can relax an immediate liquidity constraint and help a household meet an unexpected expense, but the loan must subsequently be repaid. Any short-term consumption-smoothing gain may therefore be partly offset by future repayment obligations. This helps explain why mobile banking loans are associated with improved emergency-fund access and financial planning, but do not generate the broad improvements in food security, medical access, and financial endurance observed for digital savings.

The pooled IPWRA estimates show no statistically significant improvement in food security, medical access, or financial endurance. PSM suggests a modest reduction of 2.6–3.3 percentage points in the probability of going without sufficient food, but the corresponding IPWRA estimate is not significant. This divergence warrants a cautious interpretation: formal digital credit may provide temporary consumption support for some borrowers, but the evidence is not sufficiently consistent to conclude that it improves food security across the full sample. Similarly, the lack of a durable financial-endurance effect indicates that access to formal credit does not necessarily improve households' ability to make income last between receipt periods.

The wave-specific estimates in Annex Tables B1–B7 show that several positive coefficients are concentrated in select survey years. These temporal differences may reflect changes in product design, borrower composition, macroeconomic conditions, or the types of shocks households faced. The pooled results are therefore best interpreted as the average relationship across the three survey rounds, while the Annex provides the detail required to assess whether specific effects were persistent or episodic. Relative to digital savings, mobile banking loans appear to offer a narrower but still meaningful resilience function centered on formal, short-term liquidity access.

4.3.3 App-based digital loans and mobile provider loans: Mixed to negative effects

Mobile provider loans and app-based digital loans produce less favorable and less consistent results. Mobile provider loans are associated in the pooled IPWRA estimates with modest improvements in medical access, saving for emergencies, and financial planning. However, PSM consistently confirms only the improvement in financial planning and the small reduction in difficulty accessing medical care; effects on the remaining outcomes are weak or statistically insignificant. This suggests that provider-based credit may offer limited convenience or short-term liquidity, but it does not translate into a broad improvement in household coping capacity.

App-based digital loans show the clearest adverse associations. In the pooled IPWRA estimates, their use reduces the probability of saving for emergencies by 4.3 percentage points and financial endurance by 6.5 percentage points. PSM likewise indicates substantial reductions in financial endurance, ranging from 6.5 to 9.8 percentage points, and provides no robust evidence of improved emergency saving. These are among the largest negative effects in the analysis and imply that the costs associated with app-based borrowing may persist beyond the point of disbursement.

The likely mechanism is that short maturities, high effective borrowing costs, automated deductions, and repeated borrowing reduce the disposable resources available between income periods. In that setting, digital credit may ease an immediate cash shortage while weakening the household's subsequent ability to build precautionary balances or stretch income over time. This interpretation is consistent with evidence from Kenya that easy access to digital credit can coexist with over-borrowing, repayment stress, and consumer-protection concerns (FSD Kenya et al. 2019; Johnen et al. 2021; Upadhyaya et al. 2025). It also aligns with findings that digital loans may expand short-term liquidity without building durable saving capacity (Suri et al. 2021).

Some PSM specifications associate app-based loans with improved financial planning, emergency-fund access, or food security. These estimates, however, are not consistently reproduced by IPWRA or across matching algorithms. The pooled evidence therefore does not support a general coping-capacity benefit from app-based lending. The year-specific estimates in Annex Tables B1–B7 also reveal substantial variation across 2019, 2021, and 2024, including more favorable estimates in the earliest wave. This may reflect a shift from a relatively selected group of early adopters toward a broader and potentially more financially vulnerable borrower base as the market expanded.

In sum, these estimates show that the type and function of a DFS product matter more for household resilience than digital access alone. Savings products generate the broadest and most robust gains because they support both ex ante preparation and ex post coping without creating a repayment burden. Formal mobile banking credit provides more targeted benefits, particularly for financial planning and emergency liquidity. Mobile provider credit produces only limited improvements, while app-based lending is associated with weaker emergency saving and financial endurance. Aggregating these products into a single measure of digital financial inclusion would therefore obscure policy-relevant economic differences in how households manage shocks.

Table 3: Average treatment effects on the treated inverse probability-weighting-regression-adjustment estimates for the effects of digital financial services on different household coping mechanisms

Digital financial product	**Coping Mechanisms**						
	Going without sufficient food to eat	**Difficulty in accessing medical care when needed**	**Saving for emergencies**	**Financial planning**	**Goal-oriented savings**	**Accessing emergency funds**	**Financial endurance**
Savings through mobile banking	-0.040***	-0.027***	0.140***	0.071***	0.080***	0.075***	0.028***
Savings through mobile money provider	-0.019***	-0.033***	0.104***	0.093***	0.044***	0.042***	0.003
Loan from mobile banking	-0.017	-0.009	0.037***	0.051***	0.025**	0.043***	0.016
Loan from mobile provider	-0.007	-0.012**	0.019**	0.035***	0.006	0.006	-0.003
Digital app loans	-0.013	0.008	-0.043*	0.029	-0.021	0.037*	-0.065***

Note: Significance levels; *** 1%, ** 5%, * 10%

Source: Authors' compilation from FinAccess 2019, 2021, and 2024 data.

Table 4: Average treatment on the treated propensity-score-matching estimates for the effects of digital financial services on different household coping mechanisms

Digital financial product	Matching algorithm	Coping Mechanisms						
		Going without sufficient food to eat	Difficulty in accessing medical care when needed	Saving for emergencies	Financial planning	Goal-oriented savings	Accessing emergency funds	Financial endurance
Savings through mobile banking	NNM	-0.26***	-0.022***	0.095***	0.078***	0.056***	0.077***	0.031***
	Kernel matching	-0.047***	-0.028***	0.109***	0.076***	0.060***	0.085***	0.028***
Savings through mobile money provider	NNM	-0.021***	-0.028***	0.056***	0.099***	0.029***	0.037***	-0.001
	Kernel matching	-0.023***	-0.035***	0.066***	0.95***	0.036***	0.047***	0.006
Loan from mobile banking	NNM	-0.033**	-0.015	0.011	0.061***	0.014	0.059***	0.017
	Kernel matching	-0.026**	-0.011	0.026**	0.061***	0.019	0.049***	0.015
Loan from mobile provider	NNM	-0.007	-0.01	-0.004	0.032***	-0.013	0.004	-0.005
	Kernel matching	-0.01	-0.014**	0.009	0.036***	0.001	0.006	-0.003
Digital app loans	NNM	-0.032	0.02	-0.039	0.055*	-0.081**	0.013	-0.098***
	Kernel matching	-0.062**	-0.007	-0.005	0.066***	-0.017	0.076***	-0.065***

Note: Significance levels; *** 1%, ** 5%, * 10%

Source: Authors' compilation from FinAccess 2019, 2021, and 2024 data.

Note: NNM = nearest-neighbor matching.

5. Conclusions

The findings from this paper make three specific contributions to the literature. First, they extend the foundational work of Jack and Suri (2014) and Suri and Jack (2016), which established that mobile money improves risk sharing and reduces poverty in Kenya, by disaggregating these relationships across product types and a broader set of outcomes on household coping capacity. Whereas those studies focused primarily on M-Pesa's person-to-person transfer function, this paper examines digital savings, mobile banking, mobile provider loans, and app-based digital credit within a unified empirical framework. The results demonstrate that digital financial inclusion is not a homogeneous intervention: the direction, magnitude, and consistency of its associations with household coping capacity depend strongly on the specific financial function and delivery channel.

Second, the paper builds on the findings of Suri et al. (2021), whose research found that M-Shwari digital loans improved one dimension of coping capacity but had no significant effect on consumption or savings. Our findings corroborate and extend this result across seven coping-capacity indicators and several digital credit products. Digital savings produce the broadest and most robust positive associations. Mobile banking savings are associated with a 14-percentage-point increase in saving for emergencies, an 8-percentage-point increase in goal-oriented saving, a 7.5-percentage-point increase in access to emergency funds, and a 7.1-percentage-point increase in financial planning. These savings are also associated with reductions of 4 percentage points in food insecurity and 2.7 percentage points in difficulty accessing needed medical care. Mobile money savings show associations that are similarly positive, although generally smaller, across most outcomes. The consistency of these results across IPWRA and PSM strengthens confidence in the central pattern, although the estimates should be interpreted as adjusted associations among observationally similar households rather than unconditional causal effects.

Third, the paper provides a multi-wave, product-level account of both DFS adoption and household coping capacity in Kenya's rapidly changing digital finance market. The adoption results show that access to digital infrastructure remains the most important correlate of participation. Mobile phone ownership is associated with increases of 48 percentage points in the probability of using mobile money savings, 23.6 percentage points in the use of mobile provider loans, and 22 percentage points in mobile banking savings. Internet access raises adoption probabilities by a further 1.7–5.9 percentage points across products. These findings confirm that the digital divide remains closely intertwined with the divide in financial inclusion.

Adoption is also strongly stratified by education, gender, livelihood, financial experience, and geography. Postsecondary education is associated with increases of 7.3–12.7 percentage points in the use of the four main savings and credit products relative to having no formal education. Men are 1.2–3.6 percentage points more likely than women to adopt most products, while residents of northeastern Kenya are 9.6–

19.4 percentage points less likely than Nairobi residents to use the major savings and credit products. Self-employed respondents are more likely than salaried workers to use mobile banking savings, mobile money savings, and mobile banking loans, whereas casual and seasonal workers are less likely to use bank-linked products. Prior loan default is also strongly associated with continued DFS use, particularly mobile banking loans and mobile provider loans, where adoption probabilities are higher by 12.3 and 17.6 percentage points, respectively. This pattern may reflect prior exposure to digital borrowing, repeated credit demand, or continuing financial distress and therefore warrants attention from both regulators and providers.

The findings carry several actionable implications for regulators, DFS providers, and development partners working on financial inclusion in Kenya and comparable sub-Saharan African settings. First, financial inclusion strategies should prioritize savings-led DFS models. The evidence does not show that every savings product improves every coping outcome, but it does show that digital savings generate substantially broader and more consistent gains than digital credit. Policymakers and development partners should assess whether incentives for DFS providers, including regulatory sandboxes, public-private partnerships, and financial capability programs, adequately support the development and use of affordable, flexible, and accessible digital savings products. The commercial attractiveness of high-margin digital lending may otherwise result in the undersupply of savings products relative to their potential social value.

Second, consumer protection in the digital credit market should be strengthened. App-based loans are associated with a 4.3-percentage-point reduction in emergency savings and a 6.5-percentage-point reduction in financial endurance under IPWRA, while matching estimates indicate reductions in financial endurance of between 6.5 and 9.8 percentage points. These findings suggest that easy access to short-term liquidity can coexist with weaker financial preparedness and greater pressure on household cash flow. By contrast, formal mobile banking loans produce narrower positive associations, particularly for financial planning and emergency-fund access, but do not generate the broad improvements observed for savings products. This distinction highlights the importance of differentiating between formal bank-linked credit, mobile provider credit, and app-based lending in regulation and policy design.

Effective digital credit regulation should therefore include clear disclosure of total borrowing costs, affordable and transparent repayment structures, safeguards against excessive automated deductions, stronger real-time credit information sharing, and accessible grievance-redress mechanisms. Particular attention should be given to repeat borrowers and previous defaulters, who appear substantially more likely to remain engaged in digital credit markets and may face heightened risks of debt cycling and financial stress.

Third, policies should address the structural barriers that continue to exclude disadvantaged groups from the DFS products with the strongest positive associations.

The persistent gaps by gender, education, income, livelihood, and geography indicate that DFS expansion has not been self-equalizing. Affordable phone ownership, reliable rural connectivity, agent and formal banking infrastructure, financial and digital literacy, and gender-responsive product design are therefore complementary requirements rather than optional additions to financial inclusion policy. The particularly large gaps in northeastern Kenya suggest a need for geographically targeted approaches rather than reliance on national-level market diffusion alone.

Fourth, providers should design products around the cash-flow realities of different user groups. Self-employed respondents and farmers may value flexible savings and transaction tools that accommodate irregular receipts, while casual and seasonal workers may require products with low minimum balances, flexible contribution schedules, and repayment terms aligned with volatile incomes. Product suitability should therefore be assessed not only by the number of accounts opened, but also by sustained use, affordability, consumer outcomes, and contribution to financial preparedness.

Overall, the rapid expansion of DFS across sub-Saharan Africa represents one of the most significant shifts in household finance in recent decades. The central policy question is no longer simply whether households have access to DFS, but which products they use, on what terms, and whether those products strengthen or weaken their ability to manage shocks. The findings show that savings-oriented digital services are most consistently associated with stronger financial planning, emergency preparedness, and access to liquidity without creating a repayment burden. Formal digital credit may provide targeted short-term support, while app-based credit can undermine emergency saving and financial endurance.

Financial inclusion indicators that aggregate savings, payments, and credit into a single DFS measure risk concealing these economically important differences. Future research should therefore continue to distinguish among product types, examine the mechanisms through which households use them, and exploit panel data, randomized interventions, or natural experiments where possible to strengthen causal identification. Particular attention should also be given to the longer-term consequences of repeat digital borrowing, product regulation, and the interaction between digital access, gender, livelihoods, and geography.

6. References

Aker, J. C., Boumnijel, R., McClelland, A., and Tierney, N. (2016). Payment mechanisms and antipoverty programs: Evidence from a mobile money cash transfer experiment in Niger. Economic Development and Cultural Change, 65(1), 1–37.

Apeti, A. E. (2023). Household welfare in the digital age: Assessing the effect of mobile money on household consumption volatility in developing countries. World Development, 161, 106110.

Agarwal, S., Alok, S., Ghosh, P., & Gupta, S. (2020). Financial inclusion and alternate credit scoring: Role of big data and machine learning in FinTech. *Indian School of Business Working Paper*.

Banerjee, A., Duflo, E., Imbert, C., Mathew, S., and Pande, R. (2016). E-governance, accountability, and leakage in public programs: Experimental evidence from a financial management reform in India. American Economic Journal: Applied Economics, 8(4), 1–37.

Bharadwaj, P., Jack, W., & Suri, T. (2019). Fintech and household resilience to shocks: Evidence from digital loans in Kenya. *National Bureau of Economic Research Working Paper, 25604*.

Björkegren, D., & Grissen, D. (2020). Behavior revealed in mobile phone usage predicts credit repayment. *The World Bank Economic Review, 34*(3), 618–634.

Demirgüç-Kunt, A., Klapper, L., Singer, D., and Ansar, S. (2022). The Global Findex Database 2021: Financial inclusion, digital payments, and coping capacity in the age of COVID-19. World Bank Group.

Diallo, T. (2025). Mobile money and household coping capacity to food insecurity in Rural Mali: The role of livelihood strategies and digital transfers. Journal of the Saudi Society of Agricultural Sciences, 24, Article 26.

Dupas, P., & Robinson, J. (2013). Savings constraints and microenterprise development: Evidence from a field experiment in Kenya. *American Economic Journal: Applied Economics, 5*(1), 163–192

Field, E., Pande, R., Papp, J., and Rigol, N. (2013). Does the classic microfinance model discourage entrepreneurship among the poor? American Economic Review, 103(6), 2196–2226.

FinScope Survey 2016: Financial inclusion and usage in Rwanda. National Institute of Statistics Rwanda.

FSD Kenya. (2012). 2012 annual report. Nairobi, Kenya: FSD Kenya.

FSD Kenya. (2018). 2017 annual report. Nairobi, Kenya: FSD Kenya.

FSD Kenya. (2019). Digital credit in Kenya: Evidence from demand-side surveys. Financial Sector Deepening Kenya.

FSD Kenya. (2024). 2024 FinAccess Household Survey. Financial Sector Deepening Kenya.

Gakpa, L.-L. (2023). Financial inclusion and entrepreneurship in six Sub-Saharan African countries: Evidence from FinAccess and FinScope survey data. African Economic Research Consortium.

CGAP. (2019). *Making digital credit truly responsible: Insights from Kenya*. Consultative Group to Assist the Poor.

Giné, X., Goldberg, J., and Yang, D. (2012). Credit market consequences of improved personal identification: Field experimental evidence from Malawi. American Economic Review, 102(6), 2923–2954.

Greene, W. H. (2018). Econometric Analysis (8th ed.). Pearson.

GSMA. (2016). *State of the industry report on mobile money: Decade edition, 2006 to 2016*. GSM Association.

GSMA. (2024). *The mobile economy Sub-Saharan Africa 2024*. GSM Association.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. The Review of Economic Studies, 64(4), 605–654.

Hernán, M. A., and Robins, J. M. (2020). Causal inference: What if. Chapman and Hall/CRC.

Hirano, K., Imbens, G. W., and Ridder, G. (2003). Efficient estimation of average treatment effects using the estimated propensity score. Econometrica, 71(4), 1161–1189.

Hosmer, D. W., Lemeshow, S., and Sturdivant, R. X. (2013). Applied Logistic Regression (3rd ed.). Wiley.

IFAD. (2020). Remittances and COVID-19: Sustaining Lifelines for Poor Households.

Imbens, G. W., and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. Journal of Economic Literature, 47(1), 5–86.

Jack, W., and Suri, T. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. American Economic Review.

Johnen, C., Parlasca, M., and Mußhoff, O. (2021). Promises and pitfalls of digital credit: Empirical evidence from Kenya. PLoS ONE, 16(7), e0255215

Kaffenberger, M., Totolo, E., and Soursourian, M. (2018). A digital credit revolution: Insights from borrowers in Kenya and Tanzania. CGAP.

Karlan, D., and Zinman, J. (2009). Observing unobservables: Identifying information asymmetries with a consumer credit field experiment. Econometrica, 77(6), 1993–2008.

Karlan, D., Ratan, A. L., and Zinman, J. (2016a). Savings by and for the poor: A research review and agenda. Review of Income and Wealth, 62(1), 66–122.

Karlan, D., Kendall, J., Mann, R., Pande, R., Suri, T., and Zinman, J. (2016b). Research and impacts of digital financial services. National Bureau of Economic Research.

Karlan, D., McConnell, M., Mullainathan, S., and Zinman, J. (2011). Getting to the top of mind: How reminders increase saving. National Bureau of Economic Research Working Paper No. 16205

Kikulwe, E. M., Fischer, E., and Qaim, M. (2014). Mobile money, smallholder farmers, and household welfare in Kenya. *PLoS ONE, 9*(10), e109804.

Kirui, O. K., Okello, J. J., Nyikal, R. A., and Njiraini, G. W. (2013). Impact of mobile phone-based money transfer services in agriculture: Evidence from Kenya. Quarterly Journal of International Agriculture, 52(2), 141–162.

Klapper, L., El-Zoghbi, M., & Hess, J. (2016). *Achieving the sustainable development goals: The role of financial inclusion*. Consultative Group to Assist the Poor (CGAP).

Lonie, S., Martinez, M., Oulai, R., and Tullis, C. (2018). Opportunities for Digital Financial Services in the Cocoa Value Chain in Côte d'Ivoire: Insights from New Data. Washington, DC: World Bank Group.

Miller, M., Reichelstein, J., Salas, C., and Zia, B. (2014). Can you help someone become financially capable? A meta-analysis of the literature. World Bank Research Observer, 30(2), 220–246.

Munyegera, G. K., and Matsumoto, T. (2016). Mobile money, remittances, and household welfare: Panel evidence from rural Uganda. *World Development, 79*, 127–137.

Munyegera, G. K., and Matsumoto, T. (2018). ICT for financial access: Mobile money and the financial behavior of rural households in Uganda. *Review of Development Economics, 22*(1), 45–66.

Muthiora, B. (2015). Enabling mobile money policies in Kenya: The role of the central bank. GSMA Mobile Money for the Unbanked Report

Ozili, P. K. (2018). Digital finance and financial inclusion in Africa. International Journal of Economics and Financial Issues, 8(6), 1–10.

Pazarbasioglu, C., Mora, A. G., Uttamchandani, M., Natarajan, H., Feyen, E., and Saal, M. (2020). Digital Financial Services. World Bank Group.

Rosenbaum, P. R., and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41–55.

Riley, E. (2018). Mobile money and risk sharing against village shocks. *Journal of Development Economics, 135*, 43–58.

Suri, T., and Jack, W. (2016). The long-run poverty and gender impacts of mobile money. Science, 354(6317), 1288–1292.

Suri, T. (2017). Mobile money. *Annual Review of Economics, 9*, 497–520.

Suri, T., Bharadwaj, P., and Jack, W. (2021). Fintech and household coping capacity to shocks: Evidence from digital loans in Kenya. Journal of Development Economics, 153, 102697

Tay, Lee-Ying, Hen-Toong Tai, and Gek-Siang Tan. "Digital financial inclusion: A gateway to sustainable development." *Heliyon* 8, no. 6 (2022).

Upadhyaya, R., Weitzberg, K., and Bonyo, L. (2025). Digital credit providers, regulatory frameworks, and structural power: A case study of digital microcredit regulation in Kenya. Finance and Society, 11(2), 186–208.

Wairimu, E. (2025). Digital finance and agri-food value chains: Case studies from Kenya. International Food Policy Research Institute (IFPRI).

Wieser, C., and Bruhn, M. (2018). A randomized controlled trial brings evidence on how mobile money can improve livelihoods even in very poor and remote areas. World Bank.

World Bank. (2020). Digital Financial Inclusion in Nigeria: State of the Market and Policy Recommendations. World Bank.

Zetzsche, D. A., Buckley, R. P., Arner, D. W., and Barberis, J. N. (2019). From FinTech to TechFin: The regulatory challenges of data-driven finance. New York University Journal of Law and Business, 14(2), 393–446.

Annex

A: Logistic regression tables for correlates of adopting digital financial services

A1: Determines of adoption of mobile banking savings

Variables	Savings_mobilebank_Marginal effects			
	2019	**2021**	**2024**	**Pooled**
Age	-0.00115	-0.00144***	-0.00295***	-0.00165***
log_income	0.0453***	0.0153***	0.0238***	0.0156***
Type_dwelling_unit: Permanent building				
Semi-permanent		-0.0209***	0.0152	-0.0182***
Temporary		-0.0343***	-0.0154	-0.0389***
Traditional		-0.0711***	0.00437	-0.0587***
asset_index_0_100		0.00103***	0.000600	0.000989***
total_TLU		-0.000530	0.00231	-0.000318
HH_size	-0.00422	-0.00237*	-0.00312	-0.00221*
Rural	0.00292	0.00923*	-0.0259	0.00448
Male	-0.0121	0.00968**	0.0308**	0.0127***
Educ: None				
Primary	0.0406	0.0698***	0.0880***	0.0718***
Secondary	0.0862**	0.103***	0.113***	0.104***
Postsecondary	0.0752*	0.123***	0.151***	0.126***
Goal: Putting food on the table				
Educating yourself or your family	0.0147	0.0205***	-0.00430	0.0168***
Starting/Improving your business/farm/livestock	0.0317	0.0209***	0.0245	0.0216***
Health (yourself or family/ others)	0.0532*	-0.00974	-0.00822	-0.0125
Other goals	0.0320	0.0311***	-0.0217	0.0231***
Decision_maker: Self				
Spouse	-0.0383	-0.0209**	0.00366	-0.0201***
Jointly (with spouse)	-0.0338*	0.0106*	0.00110	0.00893
Others	0.0109	-0.0244***	0.0725***	-0.0161**
source_income: Employee				
Farming (crops, keeping livestock, fishing, aquaculture)	-0.00693	-0.0143		-0.0124
Casual worker/Seasonal Worker	-0.0361	-0.0194**	-0.0193	-0.0199***
Running own business/Self employed	-0.0180	0.0325***	0.0118	0.0273***
Others	-0.0299	-0.0310***	-0.0226	-0.0319***
Mobile	0.168**	0.212***	0.280***	0.220***
Internet_access	0.0963***	0.0599***	0.0561***	0.0586***
Defaulted	0.0171	0.0568***	0.0501***	0.0556***
Receive_financial_assistance	-0.0224	-0.00307	0.00616	-0.00301
Lack_schoolfees	-0.0541***	-0.0156***	0.0141	-0.0132***

Variables	Savings_mobilebank_Marginal effects			
	2019	**2021**	**2024**	**Pooled**
Improved_Financial_status	-0.00675	-0.00165	0.0172	0.00353
Region: Nairobi				
Coast	-0.173***	-0.0506***	0.0281	-0.0475***
Northeastern	-0.306***	-0.133***	-0.0273	-0.131***
Eastern	-0.253***	-0.0867***	0.0470	-0.0776***
Central	-0.176***	-0.0595***	-0.00993	-0.0597***
Rift Valley	-0.200***	-0.0513***	0.0298	-0.0476***
Western	-0.128***	0.0431***	0.0774*	0.0359**
Nyanza	-0.151***	-0.0148	0.0232	-0.0167
Observations	1,733	19,474	2,700	22,174

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A2: Determines of adoption of mobile money savings

Variables	Savings_mobilemoney_ Marginal Eeffects			
	2019	**2021**	**2024**	**Pooled**
Age	-0.000926	-0.000298	-0.00107	-0.00104***
log_income	0.0416***	0.0137***	0.0337***	0.0122***
Type_dwelling_unit: Permanent building				
Semi-permanent		-0.0328***	0.0405*	-0.0210***
Temporary		-0.0217*	0.0542*	-0.0297**
Traditional		-0.0386**	0.243***	-0.0254
Asset_index_0_100		0.00134***	0.00216	0.00178***
total_TLU		-0.000612	0.000886	-0.000701
HH_size	-0.0233***	-0.00407**	-0.00167	-0.00422***
Rural	-0.0319	0.0314***	-0.0235	-0.00232
Male	0.0960***	0.0200***	0.0309	0.0223***
Educ: None				
Primary	0.0956**	0.0633***	0.139***	0.0596***
Secondary	0.0774*	0.0709***	0.125***	0.0659***
Postsecondary	0.0132	0.0898***	0.0577	0.0730***
Goal: Putting food on the table				
Educating yourself or your family	0.00183	0.0208**	0.0295	0.0166**
Starting/Improving your business/farm/livestock	0.0166	0.00482	0.0509*	0.00245
Health (yourself or family/ others)	-0.0158	-0.0308**	-0.0117	-0.0375***
Other goals	-0.0372	0.0406***	0.0397	0.0321***
Decision_maker: Self				
Spouse	0.0709**	-0.0104	-0.0160	-0.0293***
Jointly (with spouse)	0.0104	-0.00568	0.00978	-0.00781
Others	-0.00154	-0.0847***	-0.0319	-0.0794***
source_income: Employee				
Farming (crops, keeping livestock, fishing, aquaculture)	-0.0319	0.0186		0.0712***
Casual worker/Seasonal Worker	-0.0295	-0.0101	0.0506*	-0.00594
Running own business/Self employed	0.0126	0.0661***	0.112***	0.0666***
Others	-0.0909*	-0.0463***	0.0512	-0.0304**
Mobile	0.391***	0.477***	0.415***	0.480***
Internet_access	0.0475*	0.0484***	0.0225	0.0307***
defaulted	-0.000653	0.0724***	0.00127	0.0559***
Receive_financial_assistance	-0.116***	-0.0390***	-0.0499**	-0.0377***
Lack_schoolfees	-0.0572**	-0.0137*	0.00652	-0.0140**
Improved_Financial_status	0.00521	0.0462***	0.0629***	0.0151
Region: Nairobi				
Coast	-0.185***	-0.0695***	-0.240**	-0.0809***
Northeastern	-0.166**	-0.158***	-0.398***	-0.168***

Variables	Savings_mobilemoney_ Marginal Eeffects			
	2019	**2021**	**2024**	**Pooled**
Eastern	0.00714	-0.0900***	-0.245***	-0.0981***
Central	-0.167***	0.0223	-0.282***	-0.00159
Rift Valley	-0.353***	-0.0499**	-0.210**	-0.0606***
Western	-0.112**	0.0371*	-0.224**	0.00156
Nyanza	-0.175***	0.00202	-0.363***	-0.0335
Observations	1,733	19,474	2,700	22,174

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

A3: Determines of adoption of mobile banking loans

Variables	Loan_mobilebanking_ Marginal effects			
	2019	2021	2024	Pooled
Age	0.00204***	0.000204	0.00167***	0.000309**
log_income	0.0313***	0.00537***	0.0127**	0.00546***
Type_dwelling_unit: Permanent building				
Semi-permanent		-0.0123***	-0.0331**	-0.0139***
Temporary		-0.0186**	-0.0331*	-0.0280***
Traditional		-0.0571***	-0.0562**	-0.0582***
asset_index_0_100		0.000874***	0.000815	0.000900***
total_TLU		-0.000537	-1.02e-05	-0.000605
HH_size	0.00109	-0.00191*	0.00398	-0.00127
Rural	-0.0153	-0.00402	0.00960	-0.00606
Male	-0.00614	0.0101**	0.0275**	0.0116***
Educ: None				
Primary	0.0551***	0.0430***	0.0688***	0.0452***
Secondary	0.111***	0.0703***	0.103***	0.0735***
Post-Secondary	0.109***	0.0850***	0.0843***	0.0827***
Goal: Putting food on the table				
Educating yourself or your family	0.0352**	-0.00220	0.0290**	0.000873
Starting/Improving your business/farm/livestock	0.0664***	0.00384	0.0342**	0.00641
Health (yourself or family/ others)	0.0208	0.00161	-0.00283	-0.000612
Other goals	0.0994***	0.0127**	0.0297*	0.0128**
Decision_maker: Self				
Spouse	-0.0179	-0.0294***	0.0187	-0.0264***
Jointly (with spouse)	-0.0191	0.00302	0.00212	0.00259
Others	0.0155	-0.0293***	-0.0446***	-0.0303***
source_income: Employee				
Farming (crops, keeping livestock, fishing, aquaculture)	-0.0147	-0.0147**	-0.00940	-0.0143**
Casual worker/Seasonal Worker	-0.00491	-0.0150**	-0.00710	-0.0167***
Running own business/Self employed	0.0166	0.0197***	-0.0206	0.0136**
Others	-0.0334	-0.0172**	0.110**	-0.0181***
mobile	0.127*	0.108***	0.0404***	0.108***
Internet_access	0.0968***	0.0354***	0.0988***	0.0343***
defaulted	0.0684***	0.127***	0.0117	0.123***
Receive_financial_assistance	0.0111	0.00949**	0.0140	0.00975**
Lack_schoolfees	-0.00676	0.00991**	-0.0131	0.00980**
Improved_Financial_status	0.0120	-0.00342		-0.0104*
Region: Nairobi				
Coast	-0.0766**	-0.0124	-0.0329	-0.0170
Northeastern	-0.159***	-0.0970***		-0.0960***

Variables	Loan_mobilebanking_ Marginal effects			
	2019	2021	2024	Pooled
Eastern	-0.104***	-0.0384***	-0.0158	-0.0363***
Central	-0.0679**	-0.00428	0.0304	-0.00252
Rift Valley	-0.0234	-0.0295**	0.0185	-0.0261**
Western	-0.0546*	0.0262**	0.0118	0.0183
Nyanza	-0.0368	-0.0145	-0.00885	-0.0162
Observations	1,733	19,474	2,650	22,174

*** p<0.01, ** p<0.05, * p<0.1

A4: Determines of adoption of digital application loans

Digital_loan_ marginal effects				
Variables	**2019**	**2021**	**2024**	**Pooled**
Age	-0.00213***	- 0.000421***	5.23e-05	-0.000379***
log_income	0.000983	0.00385***	0.00186	0.00347***
Type_dwelling_unit: Permanent building				
Semi-permanent		-0.00183	-0.00649	-0.00204
Temporary		0.00356	-0.00884	-0.00124
Traditional		-0.00397		-0.00865
asset_index_0_100		7.59e-05	-0.000125	6.02e-05
total_TLU		-0.000713	0.000687	-0.000418
HH_size	-0.0113**	-0.00104*	0.00150	-0.000782
Rural	-0.0122	-0.00719***	-0.00436	-0.00758***
Male	-0.00564	0.00240	0.00342	0.00203
Educ: None				
Primary	0.0340	0.00847***		0.00789***
Secondary	0.0344	0.0162***		0.0163***
Postsecondary	0.0819*	0.0290***		0.0280***
Goal: Putting food on the table				
Educating yourself or your family	0.0843***	-0.00107	-0.0226**	-0.00329
Starting/Improving your business/farm/livestock	0.0510*	-0.000567	-0.0132	-0.00176
Health (yourself or family/ others)	0.0255	0.000964	-0.0147	-0.000110
Other goals	0.0995***	0.000423	-0.00273	-0.000308
Decision_maker: Self				
Spouse	-0.00137	-0.00160	-0.000882	-0.00273
Jointly (with spouse)	0.0229	-0.000503	-0.00659	-0.00146
Others	0.0138	0.000149	0.00265	0.000683
source_income: Employee				
Farming (crops, keeping livestock, fishing, aquaculture)	0.0155	-0.00176		-0.00213
Casual worker/Seasonal Worker	0.0420	0.00291	-0.00799	0.00127
Running own business/Self employed	0.0590**	0.00699**	-0.00555	0.00519*
Others	0.0849**	0.00378	-0.0203**	0.00162
mobile	0.0789**	0.0170*		0.0183*
Internet_access	0.0491***	0.0185***	0.0102	0.0172***
defaulted	0.0932***	0.0359***	0.0199***	0.0334***
Receive_financial_assistance	0.0650***	-0.00148	-0.00164	-0.00117
Lack_schoolfees	0.0112	-0.00176	0.00394	-0.00140
Improved_Financial_status	0.0260	-4.55e-05	-0.0141*	-0.00374

Digital_loan_ marginal effects				
Variables	**2019**	**2021**	**2024**	**Pooled**
Region: Nairobi				
Coast	0.0514*	-0.00651		-0.00518
Northeastern		-0.0229***		-0.0213***
Eastern	0.170***	-0.00385		-0.00296
Central	0.125***	-0.00102		-0.000204
Rift Valley	-0.0337	-0.00688		-0.00541
Western	0.133***	0.000547		-0.000943
Nyanza	-0.0476**	-0.00900*		-0.00714
Observations	1,518	19,474	2,130	22,174

*** p<0.01, ** p<0.05, * p<0.1

A5: Determines of adoption of mobile provider loans

Variables	Loan_mobileprovider_ Marginal effects		
	2021	2024	Pooled
Age	-0.00282***	-0.000488	-0.00250***
log_income	0.0101***	0.0125	0.0104***
Type_dwelling_unit: Permanent building			
Semi-permanent	-0.00374	0.00534	-0.00180
Temporary	-0.0356***	0.00829	-0.0340***
Traditional	-0.0477***	-0.0678**	-0.0472***
asset_index_0_100	-0.000757**	-0.00103	-0.000826**
total_TLU	-0.000385	-0.00151	-0.000576
HH_size	-0.000862	0.00956***	0.000778
Rural	-0.0178***	-0.000723	-0.0165***
Male	0.0373***	0.0352**	0.0359***
Educ: None			
Primary	0.0934***	0.0744**	0.0939***
Secondary	0.111***	0.128***	0.116***
Postsecondary	0.127***	0.130***	0.127***
Goal: Putting food on the table			
Educating yourself or your family	-0.00515	0.0190	-0.00391
Starting/Improving your business/farm/livestock	0.0121	0.0243	0.0120
Health (yourself or family/ others)	-0.0192**	0.0506*	-0.0119
Other goals	0.0275***	0.0222	0.0242***
Decision_maker: Self			
Spouse	-0.0356***	0.0382	-0.0250***
Jointly (with spouse)	-0.000348	-0.0335*	-0.00442
Others	-0.0344***	-0.0316	-0.0361***
source_income: Employee			
Farming (crops, keeping livestock, fishing, aquaculture)	0.00277		-0.00772
Casual worker/Seasonal Worker	0.0107	-0.0404	0.00206
Running own business/Self employed	0.00937	-0.0309	0.00401
Others	-0.0117	-0.0688**	-0.0186**
mobile	0.223***	0.357***	0.236***
Internet_access	0.0348***	0.0934***	0.0423***
defaulted	0.183***	0.138***	0.176***
Receive_financial_assistance	-0.0116**	-0.000328	-0.0111**
Lack_schoolfees	-0.00205	0.0436**	0.00194
Improved_Financial_status	0.00174	-0.0165	-0.00525
Region: Nairobi			
Coast	-0.0509***	-0.0343	-0.0559***
Northeastern	-0.197***	-0.0683	-0.194***
Eastern	-0.0857***	0.0815	-0.0721***
Central	-0.0534***	0.0275	-0.0518***

Variables	Loan_mobileprovider_ Marginal effects		
	2021	2024	Pooled
Rift Valley	-0.0446***	0.0323	-0.0429***
Western	-0.0116	0.0183	-0.0180
Nyanza	-0.0759***	0.0775	-0.0633***
Observations	19,474	2,700	22,174
*** p<0.01, ** p<0.05, * p<0.1			

Annex B: Inverse-probability-weighted-regression-adjustment and propensity-score-matching estimates on the effects of digital financial service usage on household coping mechanisms

Table B1: Impact of digital financial services on food insecurity

Inverse-probability-weighted-regression adjustment estimates				
	2019	2021	2024	Pooled
Digital financial service	ATET	ATET	ATET	ATET
Savings through mobile banking	-0.05	-0.042***	-0.054**	-0.040***
Savings through mobile money provider	0.012	-0.042***	0.004	-0.019***
Loan from mobile banking	-0.01	-0.026**	0.001	-0.017
Loan from mobile provider		-0.014	0.032	-0.007
Digital app loans	-0.133***	-0.022	0.094	-0.013
Significance levels; *** 1%, ** 5%, * 10%				

Propensity-score matching estimates					
Digital financial service	Matching Algorithm	2019	2021	2024	Pooled
		ATT	ATT	ATT	ATT
Savings through mobile bank	NNM	-0.064	-0.041***	-0.049	-0.26***
	Kernel Matching	-0.044	-0.048***	-0.055**	-0.047***
Savings through mobile money provider	NNM	-0.007	-0.036***	-0.001	-0.021***
	Kernel Matching	0.009	-0.042***	0.003	-0.023***
Loan from mobile banking	NNM	0	-0.024	-0.017	-0.033**
	Kernel Matching	-0.011	-0.035**	-0.009	-0.026**
Loan from mobile provider	NNM		-0.005	0.023	-0.007
	Kernel Matching		-0.016	0.028	-0.01
Digital app loans	NNM	-0.064	-0.011	0.083	-0.032
	Kernel Matching	-0.127***	-0.071***	0.055	-0.062**
Significance levels; *** 1%, ** 5%, * 10%					

Table B2: Impact of digital financial services on household access to medical care

Inverse-probability-weighted-regression adjustment estimates				
	2019	2021	2024	Pooled
Digital financial product	ATET	ATET	ATET	ATET
Savings through mobile banking	0.059	-0.022***	-0.045***	-0.027***
Savings through mobile money provider	0.061**	-0.033***	0.002	-0.033***
Loan from mobile banking	-0.014	-0.003	-0.03	-0.009
Loan from mobile provider		-0.011**	-0.015	-0.012**
Digital app loans	-0.115***	0.011	0.002	0.008
Significance levels; *** 1%, ** 5%, * 10%				

Propensity-score matching estimates					
Digital financial product	Matching algorithm	2019	2021	2024	Pooled
		ATT	ATT	ATT	ATT
Savings through mobile banking	NNM	0.055	-0.030***	-0.039*	-0.022***
	Kernel matching	0.053	-0.024***	-0.047****	-0.028***
Savings through mobile money provider	NNM	0.038	-0.028***	-0.004	-0.028***
	Kernel matching	0.066**	-0.027***	0.001	-0.035***
Loan from mobile banking	NNM	0.012	-0.04	-0.021	-0.015
	Kernel matching	-0.02	-0.06	-0.027	-0.011
Loan from mobile provider	NNM	-	-0.015**	-0.019	-0.01
	Kernel matching	-	-0.013**	-0.016	-0.014**
Digital app loans	NNM	-0.111**	0	0	0.02
	Kernel matching	-0.105**	-0.003	-0.07	-0.007
Significance levels; *** 1%, ** 5%, * 10%					

Table B3: Impact of digital financial services on saving for emergencies

Inverse-probability-weighted-regression adjustment estimates				
	2019	2021	2024	Pooled
Digital financial product	ATET	ATET	ATET	ATET
Savings through mobile banking	0.146***	0.136***	0.142***	0.140***
Savings through mobile money provider	0.177***	0.104***	0.060***	0.104***
Loan from mobile banking	0.054	0.033**	0.03	0.037***
Loan from mobile provider		0.013	0.016	0.019**
Digital app loans	-0.004	-0.051*	-0.041	-0.043*
Significance levels; *** 1%, ** 5%, * 10%				

Propensity-score matching estimates					
Digital financial product	Matching algorithm	2019	2021	2024	Pooled
		ATT	ATT	ATT	ATT
Savings through mobile banking	NNM	0.128**	0.084***	0.109**	0.095***
	Kernel matching	0.084***	0.108***	0.095***	0.109***
Savings through mobile money provider	NNM	0.134***	0.057***	0.046*	0.056***
	Kernel matching	0.124***	0.068***	0.038	0.066***
Loan from mobile banking	NNM	-0.012	-0.011	0.054	0.011
	Kernel matching	-0.011	0.012	0.037	0.026**
Loan from mobile provider	NNM	0	0.008	0.019	-0.004
	Kernel matching	0	0.003	0.037	0.009
Digital app loans	NNM	-0.049	-0.042	0	-0.039
	Kernel matching	-0.050**	-0.014	0.06	-0.005
Significance levels; *** 1%, ** 5%, * 10%					

Table B4: Impact of digital financial service on financial planning

Inverse-probability-weighted-regression adjustment estimates				
	2019	2021	2024	Pooled
Digital financial product	ATET	ATET	ATET	ATET
Savings through mobile banking	0.052	0.069***	0.060**	0.071***
Savings through mobile money provider	0.067***	0.081***	0.090***	0.093***
Loan from mobile banking	0.005	0.055***	0.028	0.051***
Loan from mobile provider		0.037***	0.016	0.035***
Digital app loans	0.06	0.06	0.038*	0.029
Significance levels; *** 1%, ** 5%, * 10%				

Propensity-score matching estimates					
Digital financial product	Matching algorithm	2019	2021	2024	Pooled
		ATT	ATT	ATT	ATT
Savings through mobile banking	NNM	0.055	0.052***	0.065**	0.078***
	Kernel matching	0.048	0.074***	0.068***	0.076***
Savings through mobile money provider	NNM	0.080***	0.084***	0.076***	0.099***
	Kernel matching	0.098***	0.083***	0.090**	0.95***
Loan from mobile banking	NNM	0.007	0.055***	-0.004	0.061***
	Kernel matching	-0.071	0.064***	0.031	0.061***
Loan from mobile provider	NNM	0	0.025***	-0.012	0.032***
	Kernel matching	0	0.058***	0.017	0.036***
Digital app loans	NNM	0.052	0.058*	-0.083	0.055*
	Kernel matching	0.056	0.068***	0.023	0.066***
Significance levels; *** 1%, ** 5%, * 10%					

Table B5: Impact of digital financial services on goal-oriented saving

Inverse-probability-weighted-regression adjustment estimates				
	2019	2021	2024	Pooled
Digital financial product	ATET	ATET	ATET	ATET
Savings through mobile bank	0.164***	0.076***	0.109***	0.080***
Savings through mobile money provider	0.112***	0.064***	0.016	0.044***
Loan from mobile banking	0.076*	0.032**	0.033	0.025**
Loan from mobile provider		0.012	0.002	0.006
Digital app loans	0.109***	-0.017	0.079	-0.021
Significance levels; *** 1%, ** 5%, * 10%				

Propensity-score matching estimates					
Digital financial product	Matching algorithm	2019	2021	2024	Pooled
		ATT	ATT	ATT	ATT
Savings through mobile banking	NNM	0.137***	0.066***	0.084**	0.056***
	Kernel matching	0.094**	0.059***	0.079**	0.060***
Savings through mobile money provider	NNM	0.026	0.033***	0.032	0.029***
	Kernel matching	0.031	0.049***	0.024	0.036***
Loan from mobile banking	NNM	0.083	0.019	0.024	0.014
	Kernel matching	0.062	0.023*	0.022	0.019
Loan from mobile provider	NNM		0.004	-0.007	-0.013
	Kernel matching		0.004	0.014	0.001
Digital app loans	NNM	0.06	-0.019	0.15	-0.081**
	Kernel matching	0.096**	-0.016	0.109	-0.017
Significance levels; *** 1%, ** 5%, * 10%					

Table B6: Impact of digital financial services on accessing emergency funds

Inverse-probability-weighted-regression adjustment estimates				
	2019	2021	2024	Pooled
Digital financial product	ATET	ATET	ATET	ATET
Savings through mobile banking	0.043	0.078***	0.062**	0.075***
Savings through mobile money provider	-0.005	0.046***	0.082***	0.042***
Loan from mobile banking	0.061*	0.042***	0.073**	0.043***
Loan from mobile provider		0.001	0.047**	0.006
Digital app loans	0.008	0.039*	-0.013	0.037*
Significance levels; *** 1%, ** 5%, * 10%				

Propensity-score matching estimates					
	Matching	2019	2021	2024	Pooled
Digital financial product	algorithm	ATT	ATT	ATT	ATT
Savings through mobile banking	NNM	0.055	0.076***	0.101**	0.077***
	Kernel matching	0.043	0.087***	0.077**	0.085***
Savings through mobile money provider	NNM	0.019	0.040***	0.060**	0.037***
	Kernel matching	-0.015	0.050***	0.073***	0.047***
Loan from mobile banking	NNM	0.069*	0.052***	0.023	0.059***
	Kernel matching	0.052	0.048***	0.084*	0.049***
Loan from mobile provider	NNM	0	0.004	0.0249	0.004
	Kernel matching	0	0.002	0.045*	0.006
Digital app loans	NNM	0.011	0.056***	0.047	0.013
	Kernel matching	0.005	0.078***	0.004	0.076***
Significance levels; *** 1%, ** 5%, * 10%					

Table B7: Impact of digital financial services on financial endurance

Inverse-probability-weighted-regression adjustment estimates				
	2019	2021	2024	Pooled
Digital financial product	ATET	ATET	ATET	ATET
Savings through mobile banking	-0.007	0.029***	0.043	0.028***
Savings through mobile money provider	0.028	0.012*	0.037**	0.003
Loan from mobile banking	-0.025	0.021*	0.003	0.016
Loan from mobile provider		0.003	-0.034	-0.003
Digital app loans	0.09**	-0.054**	-0.04	-0.065***
Significance levels; *** 1%, ** 5%, * 10%				

Propensity-score matching estimates					
Digital financial product	Matching algorithm	2019	2021	2024	Pooled
		ATT	ATT	ATT	ATT
Savings through mobile banking	NNM	0.032	0.037***	0.036	0.031***
	Kernel matching	-0.006	0.028***	0.04	0.028***
Savings through mobile money provider	NNM	0.036	-0.001	0.050**	-0.001
	Kernel matching	0.029	0.025*	0.040**	0.006
Loan from mobile banking	NNM	-0.058	0.013	0.06	0.017
	Kernel matching	-0.017	0.019	0.004	0.015
Loan from mobile provider	NNM	0	0.004	-0.025	-0.005
	Kernel matching	0	0.002	-0.034	-0.003
Digital app loans	NNM	0.099**	-0.044	-0.036	-0.098***
	Kernel matching	0.093***	-0.058**	-0.062	-0.065***
Significance levels; *** 1%, ** 5%, * 10%					

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