MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2153-2161

Bridging the Financial Divide: The Impact of Mobile Money and Digital Lending Platforms on Household Savings and Consumption in Developing Economies

Rupam, Jyoti Deka[1], Dr Naveen Nandal[2*], Srishti Goel[3], Shreya Goel[4], Ms. Shivali Yadav[5], Dr. Rita[6]
Assistant Professor, Bharati Vidyapeeth (Deemed to be) University Institute of Management, New Delhi
Associate Professor, DIHE, Rohini, Delhi
Vivekananda Institute of Professional Studies, BA Economics (Hons.) -currently in 3rd year, Delhi
Vivekananda Institute of Professional Studies, BA Economics (Hons.) -currently in 3rd year, Delhi
Assistant Professor, Jagannath University, Bahadurgarh
Assistant Professor, JIMS, Rohini, Delhi
[*]Corresponding author Email: naveennandal22@yahoo.com

Abstract
This paper presents an empirical investigation aimed at identifying the distinct economic impacts of two segments within the Digital Financial Services (DFS) ecosystem: Mobile Money (transactional infrastructure) and Digital Lending (algorithmic credit), on household capital accumulation and consumption resilience. The study used a staggered Difference-in-Differences (DiD) identification design based on a high-frequency longitudinal sample of 18,840 household observations within 2018-2023 to isolate the causal impact of agent networks and 4G infrastructure rollout on larger trends in modernisation, taking advantage of the fact that the rollout was exogenous and spatially and temporally sequential. The findings showed a dichotomous effect. The adoption of Mobile Money had a causal effect of enhancing the depth of formal savings by 6.2 percentage points, caused through a safe storage mechanism, which was observed to be the strongest among rural households. On the other hand, although Digital Lending decreased aggregate consumption volatility by 25 per cent, the effect is localised in the middle-to-high income cohorts. In the case of the poorest quartile, high-interest digital credit did not even protect consumption, as low-cost social insurance was replaced with costly debt. These results oppose the unified approach to financial inclusion and suggest a dualistic structure in which the algorithmic lending platforms should be subject to more stringent consumer protection and debt-to-income limits, and implement more stringent payment rails universality to avoid predatory inclusion at the bottom of the pyramid.
Keywords: Mobile Money, Digital Lending, Financial Inclusion, Consumption Smoothing, Developing Economies.

1. Introduction

The quest for global universal financial inclusion has been a key feature of the global development agenda for many decades now and is underpinned by the strong body of empirical evidence that access to formal financial mechanisms is a key prerequisite for poverty reduction and macro-economic stability (World Bank, 2021; Beck et al., 2007). For much of modern economic history, the "brick-and-mortar" banking model proved structurally unable to bridge the "last mile" to rural and low-income populations in developing economies. The prohibitive transaction costs of physical branch networks, combined with the overwhelming information asymmetries that are inherent to lending to informal workers without verifiable collateral, effectively shut off large segments of the global population from the formal economy (Demirguc-Kunt & Klapper, 2013). Consequently, the poor were forced to rely on informal, insecure and often exploitative financial tools ranging from the rotating savings and credit associations (ROSCAs) to the local moneylenders, which severely limited their ability to accumulate capital or manage systemic risks (Rutherford, 2000). Over the past two decades, the finance industries have experienced change as radical in its way as mobile telecommunications and equally transformative too. This alteration is no longer merely the gilded story of any chance--it is a wholesale shift in the range of transaction technologies said to the bottom tier of the economic pyramid. The infrastructure of Digital Financial Services (DFS) is diverging in two massive and very different currents, which are changing the financial lives of those at base: First off, mobile money systems–with stores of value also being digitised through the payment rails themselves–have in many ways begun to transform lives remotest. To this end. Its standard feature is providing customers a means for converting cash into e-money in order effect remittances via SMS, and storing values securely without depending on any traditional banking account (Mbiti & Weil, 2011). Second, as well as more recently, the arrival of Digital Lending is based on algorithmic credit scoring and leads to data like talk time usage history. This is now making instant unsecured liquidity available to millions who were thought of as "bankable" before (Bjorkegren & Grissen, 2020). This technological leapfrog allows developing economies to leap out of the slow process of building physical banks. And so, with the arrival of a new financial pattern--of greatest significance, the mobile phone serves as both a branch manager and a teller and for all its a bank in one.

1.1. Problem and Motivation: Beyond Adoption to Economic Behaviour

While the explosion of DFS can be seen as a victory of technological diffusion, the conversion of such access into concrete economic resilience is a complex and debated empirical issue. High levels of adoption do not necessarily mean better financial health or welfare. The core economic behaviours of households, specifically how they accumulate savings to build assets and how they cope with consumption in the face of idiosyncratic income shocks, are being fundamentally reshaped by these tools, but the directionality of this change is neither uniform nor guaranteed (Banerjee & Duflo, 2011). The main reason for this inquiry is the gap between the theoretical promise of the concept of DFS and its unclear practice on the ground. From a theoretical standpoint, the friction-greedness of Mobile Money should lower the shadow cost of savings. By converting non-interest-bearing cash hidden "under the mattress," which is at risk of theft and the temptation of immediate spending, into secure, transferable digital assets, households should, in theory, be able to increase their savings rate (Dupas & Robinson, 2013).

On the other hand, the introduction of Digital Lending fundamentally the household's inter-temporal budget constraint. Standard economic theory implies that access to credit should enable consumption smoothing, in which households borrow against future income to sustain consumption levels during times of economic hardship or emergency (Townsend, 1994). However, ease of access to high-interest digital credit introduces high risks associated with behaviour. The immediate availability of funds may encourage impulse consumption or over-indebtedness, which can entangle vulnerable households in a cycle of debt repayment that destroys their capacity to save long-term (Karlan & Zinman, 2010). Policymakers, central banks and development agencies are currently operating with limited visibility on these trade-offs. While aggregate data is proving a rise in transaction volumes, there is a paucity of evidence on the quality of this financial inclusion. There is an urgent need to move beyond simple adoption statistics to understand the causal mechanisms at play: Does the digital transition really have the effect of fortifying household balance sheets by promoting formal savings and evening out consumption, or does it simply cause greater velocity of money while bringing new forms of financial fragility?

1.2. Literature Gap: Disentangling Mechanisms and Intersectional Heterogeneity

Despite the growing body of literature that explores the effects of fintech in developing economies, there are three key gaps that this study seeks to address.

First, prevailing studies often aggregate "digital inclusion" into one, monolithic binary variable that classifies households either as "users" or "non-users" of fintech. This approach disguises the different and often conflicting economic roles of saving and borrowing. A remittance and storage platform (Mobile Money) impacts the household budget constraint in a totally different way from a credit platform (Digital Lending). The former affects the safety and transportability of capital (Munyegera & Matsumoto, 2016), and the latter affects managing leverage and liquidity (Bharadwaj et al., 2019). Existing literature does not often tease apart these two forces in the same analytical framework, which is a difficult task to determine the nature of observed welfare changes.

Second, much of the existing evidence has the problem of causal ambiguity caused by the use of cross-sectional data. Early movers of DFS are, on average, young, rich, urban and financially literate compared to the non-movers, leading to important selection bias (Blumenstock et al., 2015). While some seminal studies have used Instrumental Variable (IV) approaches, often with distance to agents as an instrument (Jack & Suri, 2014), such instruments are losing their power as agent networks achieve ubiquity. Furthermore, few studies have actually been successful in isolating the impact of digital credit in particular, from the underlying mobile money rails.

Third, and perhaps most important, there is a "heterogeneity deficit" in the current discourse. While income levels analysis is commonplace, there is little rigorous evidence around the analysis of intersectional vulnerabilities. Specifically, the role of interaction between gender, geographic isolation (rural vs. urban) and type of DFS adopted is under-explored. For example, does digital credit enable poor female-headed households in the agrarian landscape to overcome the risk of agricultural risk (Riley, 2018) or do predatory lending practices exist because of a low digital literacy level in these regions? A good understanding of these nuanced and heterogeneous effects is fundamental in designing targeted interventions instead of blanket policies.

1.3. Contribution: Methodological Rigour and Policy Relevance

The research paper will add value to the accounting, development economics and finance literature in three main ways, which will contain original findings into the digital financial revolution. Strong Identification Approach: We use a strong quasi-experimental design in order to prove causality. We use a rich panel dataset over five years and use a Difference-in-Differences (DiD) framework that measures the beneficial effect of the staggered introduction of the two mobile money agent networks and the availability of digital credit products across the various administrative regions. The approach has the advantage of controlling both time-invariant unobservables (like regional culture or geography) and time-varying common shocks, which is useful in isolating the causal effect of DFS adoption on overall economic modernisation dynamics. Such methodological practice offers better estimations compared to plain cross-sectional comparisons used in the previous literature. Mixed Digital Services: In contrast to what had been done in other literature, which confounds different forms of digital services, the effects of Mobile Money adoption and Digital Loan uptake have been separated properly in this paper. We examine their independent and interactive impacts on two objective and independently measured dependent variables, savings depth (a ratio of formal savings to income) and consumption volatility (standard deviation of monthly household spending). This breakdown will provide a clearer explanation of the household finances by providing us with a better understanding of whether savings accumulation is being facilitated by improved storage technologies (mobile money) or consumption stability is being facilitated by access to credit. Delicate Policy Implications: Our analysis of granular heterogeneity offers evidence with specific policy implications that can be easily implemented by regulators and central banks. We explore the variation in the effect of DFS on the income distribution and gender difference. The results of our study on the disproportionate effect on vulnerable cohorts, namely low-income rural women, will provide an important guide towards developing the so-called smart policies on financial inclusion. We leave the story of access at any cost behind and promote regulatory frameworks, which are consumer-protective, transparent in digital credit pricing and specially developed financial literacy programs and infrastructure development.

2. Literature Review and Hypothesis Development

2.1 Theoretical Foundations

Introduced by three key theoretical frameworks, traditional homes and buildings, digital financial services (DFS) has dramatic consequences for household economic activities. According to these perspectives, reduced transaction costs and improved liquidity access through innovative methods of intermediation all alter the way resources are allocated over future periods by a household (Friedman, 1957; Deaton, 1991; Townsend, 1994; Diamond, 1984). Together, these perspectives make good sense of how the Permanent Income Hypothesis consumption smoothing theory |and financial intermediation theory relate. For less developed countries suffering from a lack of financial infrastructure, there are very real constraints to the management of intertemporal consumption issues. By using alternative data Digital credit platforms might partially relax these constraints and enable some short-term liquidity access (Stiglitz & Weiss, 1981; Björkegren & Grissen, 2020). Moreover, financial intermediation theory argues that digital technology reduces fixed costs and information asymmetries. As a result, there is an ongoing process of small-value savings and loans that were previously excluded from formal systems (Schumpeter, 1911; Levine, 2005).

2.2 Mobile Money and Savings Behaviour

The literature consistently discovers why mobile money affects savings, mostly because it reduces transaction costs and cash holding security risks. At the same time, mobile financial services allow a household to change some of its informal cash into digital balances that are more convenient and safer for saving transfer. This effectively lowers the cost of saving (Mbiti & Weil, 2011; Dupas & Robinson, 2013). Secure storage mechanisms, according to empirical studies using experimental and quasi-experimental designs, will increase people's willingness to save and their wealth, especially those of unbanked households (Munyegera & Matsumoto, 2016; Ky et al., 2018). Mobile money is an unambiguous signal to move away from informal savings arrangements, toward more individualised and secure financial control. (Higgins et al., 2012). However, these effects differ across contexts, representing a difference in fee structures, institutional design and the intensity of use (Batista & Vicente, 2020).

2.3. Digital Lending and Consumption Smoothing

However, the recent completion ratio for digital lending is smaller and more varied. In theory, digital credit platforms provide rapid off-site loans that allow households to smooth consumption during selling-down periods (Townsend, 1994; Bharadwaj et al., 2019). A couple of studies find that access to digital credit reduces short-term consumption volatility and enables microenterprise liquidity bootstrapping (Francis et al., 2017). Nevertheless, a growing literature has emphasised the risks of excessive reliance on credit. The form of digital lending is private, immediate, and individual. As a result, people no longer feel they are under social surveillance and are thus more likely to borrow repeatedly (Karlan & Zinman, 2010; Blechman, 2016). Evidence suggests that digital credit will crowd out informal insurance systems and internal savings, leading to long-term welfare concerns for those who are particularly financially vulnerable (Blochman, 2016; Riley, 2018).

2.4 Heterogeneity in DFS Outcomes

Research has been constantly showing tha that mobile impact i.e. DFS, is heterogeneous and varies between income levels, gender and regions. Although giant technology companies such as Tencent and Ant Financial have always said that they will benefit the poorest most, evidence from empirical studies strikes a more mixed note. In some contexts, notably among female-headed households, mobile money has been linked to poverty reduction and resilience(Suri & Jack, 2016). However, digital credit benefits tend to accrue more to higher-income and even middle-income users than to lower ones (Blumenstock et al., 2015). Gender differences are central. With mobile money, women can better control resources and their withdrawal offers them both privacy protection from whoever might seek to seize a share of that spend and enhance household expenditure distribution(Aker et al., 2016). In contrast, women may face greater constraints in digital credit markets as a result of thinner data histories or bias by algorithms. (Riley, 2018) Geographic factors also condition outcomes: the greatest effects are found in rural areas where people have limited access to traditional banking services and transaction costs are high(Mora-Rivera & Garcia-Mora, 2021).

2.5 Synthesis and Theoretical Integration

Putting it all together, these studies suggest that digital financial services (DFS) affect household financial performance through quite different channels. Mobile money primarily affects savings via charging lower transaction and security costs; this argument is in line with traditional financial intermediation and the theory of safe-storage (Dupas Robinson, 2013; Mbiti Weil, 2011). Digital lending affects intertemporal consumption by relieving liquidity constraints, as predicted by models of consumption smoothing and permanent income (Townsend 1994; Friedman 1957). Effects are not uniform, with income level, gender and geography shaping both access and outcome. The hypotheses developed below build directly on this synthesis, linking theoretical mechanisms to observable household-level financial behaviours.

2.6. Hypothesis Development

Based on the theoretical framework and the synthesised empirical evidence, this study proposes the following testable hypotheses.

Hypothesis 1 (H1)**:** Mobile Money adoption has a positive and significant causal effect on the propensity to save among households. Rationale: Grounded in the Safe Storage mechanism (Dupas & Robinson, 2013) and Financial Intermediation Theory, we expect that reducing the shadow cost of holding cash will induce a shift from informal to formal savings.

Hypothesis 2 (H2)**:** Access to Digital Lending platforms significantly reduces household consumption volatility. Rationale: Based on the Permanent Income Hypothesis and Townsend's risk-sharing model, access to instant liquidity should allow households to smooth consumption against idiosyncratic income shocks (Bharadwaj et al., 2019).

Hypothesis 3 (H3)**:** The consumption level of Mobile Money is positively influenced to a much greater magnitude among rural households than urban households. Rationale: It can be explained by the transaction cost theory; the relative efficiency increase of digital transactions is the most significant in the regions of the poorest physical infrastructure (Mora-Rivera and Garcia-Mora, 2021).

Hypothesis 4 (H4)**:** There is a low marginal benefit of Digital Lending access towards the accumulation of savings by low-income households. Reasoning: As credit facilitates consumption, over-indebtedness and high interest rate behavioral risks (Karlan and Zinman, 2010) can suffocate the ability to save by the poorest group, producing the so-called debt substitution effect.

3. Research Methodology

3.1. Data Source and Sample Construction

Using Longitudinal Financial Inclusion Survey (LFIS) nationally representative high-frequency panel data, the study examines heterogeneous effects of Digital Financial Services (DFS) on household financial outcomes. The data cover the period from 2018 to 2023, which saw rapid, unbalanced expansion of mobile money agent networks and digital lending platforms in different administrative regions. The research site is a low-middle-income developing society with high mobile household penetration (over 80 per cent of adults), widespread basic mobile service, and a rapidly maturing DFS ecosystem, while there are very few traditional banks to be found outside major urban areas. There is moderate possession of formal bank accounts at the national level but sharp urban–rural disparities, especially in branches per capita in country towns and suburbs. This institutional structure, which combines high digital access with kinder gartensque brick-and-mortar banking infrastructure, makes it possible to study how digital payment and credit technologies substitute for or complement conventional financial services. One of the distinguishing features of LFIS is that it has a financial diaries module. Information on household inflows and outflows is recorded in detail at sub-annual intervals, which makes it possible to accurately measure saving behaviour and consumption dynamics (Collins et al., 2009). The sampling design follows a two-stage cluster design with stratification, thus ensuring representation of both densely populated urban areas and remote rural villages. A total of 3,500 households were initially surveyed as population census enumeration areas. To improve data quality and the consistency of panels, consumption and income variables were each winsorized at the 1st and 99th percentiles to reduce the impact from extreme outliers (Deaton, 1997); households losing more than 20 per cent of their population over the fixed period were excluded at this stage. The final estimation sample has 3,140 households, producing a balanced panel containing 18,840 household data points. This is a larger number and more than necessary for changes in savings accumulation or fluctuation of consumption expenditure to be picked up.

3.2. Variable Definition and Measurement

The operationalisation of variables is grounded in standard development economics literature to ensure comparability and internal validity.

3.2.1. Dependent Variables

We focus on two distinct dimensions of financial health: Capital Accumulation and Consumption Resilience.

1. **Formal Savings Depth (S_{it}):** It is a ratio of formal liquid assets (in mobile wallets, bank accounts, or SACCOs) to the monthly household income. This continuous measure is different to the use of binary variables as has savings in previous researches, which only record the intensity of usage (Dupas and Robinson, 2013).
2. **Consumption Volatility** (CV_{it})**:** To measure resilience, we calculate the coefficient of variation of monthly per capita food expenditure over the preceding six months. A lower CV_{it} indicates superior consumption smoothing capabilities.
3. **Log Per Capita Consumption (C_{it}):** The natural logarithm of real monthly household consumption adjusted by regional spatial price indices as a proxy of general levels of welfare.

3.2.2. Independent Variables of Interest

We disaggregate DFS into two binary treatment indicators:

1. **Mobile Money Adoption (MM_{it}):** A dummy variable that takes the value 1 in case the household has carried out any transaction (deposit, withdrawal, or transfer) with a mobile money agent during the survey reference period, and 0 otherwise.
2. **Digital Credit Access (DC_{it}):** A dummy variable equal to 1 if the household has successfully accessed a loan through a digital platform (e.g., algorithmic fintech lender) in the current period, and 0 otherwise.

3.2.3. Control Variables

To isolate the ceteris paribus effects, we include a vector of time-varying household characteristics (X_{it}):

- **Household Head Characteristics:** Age, gender, and years of formal education.
- **Economic Factors:** Log of total household assets (land and livestock), shock exposure (dummy for illness or crop failure), and off-farm employment status.
- **Community Factors:** Distance to the nearest paved road and distance to the nearest physical bank branch.

3.3. Empirical Model: Staggered Difference-in-Differences

Given the non-random assignment of DFS access where telecom operators prioritize profitable urban areas simple OLS estimation would suffer from severe omitted variable bias. To establish causality, we exploit the staggered temporal rollout of mobile money agent networks and 4G infrastructure (a prerequisite for digital lending apps) across different districts.

We employ a Two-Way Fixed Effects (TWFE) Difference-in-Differences estimator. The baseline specification is defined as follows:

$$(Y_{it} = \alpha_i + \lambda_t + \beta_1(MM_{it}) + \beta_2(DC_{it}) + \gamma X_{it} + \epsilon_{it})$$

Where:

- Y_{it} represents the outcome variable (Savings Depth or Consumption Volatility) for household \$i\$ at time \$t\$.
- α_i denotes household fixed effects, capturing time-invariant unobservables such as risk aversion, financial literacy, or cultural propensity to save.
- λ_t denotes time fixed effects, controlling for aggregate macroeconomic shocks (e.g., inflation, national policy changes) affecting all households simultaneously.
- (MM_{it}) are the treatment indicators. The coefficients \$\beta_1\$ and \$\beta_2\$ are the parameters of interest, representing the Average Treatment Effect on the Treated (ATT).
- X_{it} is the vector of time-varying controls.
- ϵ_{it} is the idiosyncratic error term, clustered at the PSU level to account for serial correlation within communities (Bertrand et al., 2004).

3.3.1. Handling Heterogeneous Treatment Effects

Recent econometric literature (Goodman-Bacon, 2021) highlights that in staggered designs, the standard TWFE estimator can be biased if treatment effects vary over time (e.g., if early adopters benefit more than late adopters). To address this, we employ the Callaway and Sant'Anna (2021) estimator as a robustness check. This method computes group-time average treatment effects $(ATT(g,t))$and aggregates them, avoiding the "forbidden comparisons" where early treated units serve as controls for late treated units.

3.4. Identification Strategy and Validity Checks

The validity of the DiD strategy rests on the Parallel Trends Assumption: in the absence of DFS adoption, the savings and consumption trajectories of adopters and non-adopters would have evolved similarly.

3.4.1. Testing Parallel Trends

We cannot directly observe the counterfactual, but we test the plausibility of this assumption using an Event Study design. We modify the baseline equation to include leads and lags of the treatment adoption year:

$$(Y_{it} = \alpha_i + \lambda_t + \sum_{k=-3}^{3} \delta_k D_{i,t-k} + \gamma X_{it} + \epsilon_{it})$$

Here, δ_k captures the dynamic effects k years relative to adoption. For the identification to hold, the coefficients for the pre-treatment periods $(\delta_{-3}, \delta_{-2})$ must be statistically indistinguishable from zero, indicating no anticipatory effects or differential pre-trends (Angrist & Pischke, 2009).

3.4.2. Addressing Endogeneity and Selection Bias

While fixed effects (α_i) control for static selection bias (e.g., wealthier households are always more likely to adopt), time-varying endogeneity remains a threat. For instance, a household might adopt digital credit because it anticipates a future income shock (reverse causality). To mitigate this, we employ an Instrumental Variable (IV) strategy as a secondary identification check (Jack & Suri, 2014). We instrument individual adoption (\$MM_{it}\$) with the GPS-calculated distance to the nearest active mobile money agent, interacting this spatial variation with the rollout timing. The exclusion restriction posits that the physical proximity of an agent affects welfare only through the channel of DFS adoption, conditional on community fixed effects. Finally, we conduct a placebo test by randomizing the timing of "treatment" across households 1,000 times. We expect the distribution of these placebo estimates to be centered on zero, confirming that our main results are not driven by spurious correlations or structural breaks in the data-generating process (Athey & Imbens, 2017).

4. Empirical Results and Discussion

4.1. Descriptive Statistics and Sample Architecture

The presence of descriptive architecture of the panel dataset highlighted in Table 1 allows the creation of the context needed to comprehend the selection mechanics involved in Digital Financial Services (DFS) adoption. The sample size is 18,840 observations of household-period between adopters and non-adopters. The unconditional means display acute pre-treatment structural deviations. The adopters of Mobile Money (MM) have a clear socio-economic platform, they are; on average, 7.1 years younger and have much higher educational level (8.4 years as compared to 5.2 years) than their non-adopting peers. This population asymmetry is consistent with the early adopter concept of diffusion theory, in which the adoption of technology is first focused on the cognitively endowed and financially savvy groups. Most importantly, there is a colossal unconditional gap in the variable of interest, Formal Savings Depth. Formal instruments save adopters around 14.21 percent of their monthly income versus a paltry 4.52 percent of the savings of non-adopters (Difference = 9.69 pp, t=15.4). Although that points to an exceptionally high degree of correlation between digitization and capital accumulation, no confounders (that is, the wealth gap demonstrated in the Asset variable) eliminate the need to use the strict Fixed Effects strategies used in the following sections to isolate the parameter of causality. On the other hand, the digital cohort Consumption Volatility is much lower (-0.04), which provides initial descriptive validity to the risk-sharing hypothesis.

Table 1: Descriptive Statistics by Adoption Status

Variable	Description	Mean (Non-Adopters)	Mean (MM Adopters)	Difference	t-stat
Outcomes					
Savings Depth	Formal Savings / Income (%)	4.52	14.21	**9.69*** **	15.4
Cons. Volatility	Coeff. Of Variation (6 mo)	0.19	0.15	**-0.04*** **	-8.2
Log Cons.	Log Per Capita Exp.	10.21	10.85	**0.64*** **	12.1
Controls					
Age	Head of Household Age	41.3	34.2	**-7.1*** **	-9.5
Education	Years of Schooling	5.2	8.4	**3.2*** **	11.3
Assets (Log)	Land and Livestock Value	8.45	9.12	**0.67*** **	7.8
Rural	1 if Rural Location	0.65	0.55	**-0.10*** **	-5.4
Distance Bank	Km to nearest branch	12.4	11.8	-0.6	-1.2
Observations		**10,927**	**7,913**		

*Note: *** p<0.01, ** p<0.05, * p<0.1. T-tests assume unequal variances.*

4.2. The Causal Impact of Mobile Money on Capital Accumulation

Table 2 shows the findings of Two-Way Fixed Effects (TWFE) model test of Hypothesis 1. The hypothesis is to establish whether safe storage facility of mobile money is causally associated with the increased rate of savings provided the time-invariant household heterogeneity is held constant.

The coefficient of Mobile Money Adoption in (2) that contains the entire set of time-varying controls is 0.062 and statistically significant at the 1% level ($p < 0.01$).

- Economic Interpretation: The ratio of formal savings to income increases by 6.2 percentage points as a result of implementing mobile money. This effect size, which implies a more than 130% increase in formal savings mobilization, will take place in the conditions of a counterfactual baseline of about 4.5% (based on Table 1).
- Implication of the Findings: This finding validates the theoretical implication of the argument that the main obstacle to saving in the poor was not the absence of income as such, but the high transaction and security costs of physical cash. MM opens up latent savings potential by bringing down the shadow cost of deposits to close to zero.

Table 2: Fixed Effects Regression - Impact on Formal Savings Depth (H_1)

Variable	(1) Baseline FE	(2) With Controls
Mobile Money Adoption (MM_{it})	**0.068*** **	**0.062*** **
	(0.004)	*(0.005)*
Asset Shocks		-0.012**
		(0.005)
Off-Farm Employment		0.015***
		(0.004)
Constant	0.041***	0.035***
Household FE	YES	YES
Time FE	YES	YES
Observations	18,840	18,840
R-squared (Within)	0.184	0.215

*Note: Standard errors clustered at the Primary Sampling Unit (PSU) level in parentheses. *** p<0.01.*

4.3. Digital Lending and Consumption Resilience (H2)

The next item is the effect of Digital Credit (DC) on household resilience, to test the hypothesis that algorithmic loans can facilitate consumption smoothing (H2). Table 3 results give a subtle visualisation of financial resilience.

The full-specification coefficient of Digital Credit Access (-0.045, $p < 0.05$) of column 3.

- Interpretation: Digital credit access lowers the coefficient of variation in the consumption of household food by 0.045 units. This is a 25 percent enhancement in the stability in consumption as compared to the sample mean volatility of 0.18. This confirms the risk-sharing hypothesis: households take instant digital loans to smooth idiosyncratic income crises (e.g. illness, crop failure) so that consumption falls off a cliff.
- Levels vs. Volatility: Column (4) indicates that the influence on the Log Per Capita Consumption (levels) is minimal and slightly significant $\beta = 0.021, p < 0.1$. This supports the finding that digital credit is a liquidity management instrument (smoothing the curve) and not a wealth-generation instrument (moving the curve up).

Table 3: Difference-in-Differences - Impact on Consumption Volatility (H2)

Variable	(1) Baseline	(2) With Controls	(3) Full Spec	(4) Log Consumption
Digital Credit Access (DC_{it})	**-0.052*** **	**-0.049*** **	**-0.045** **	**0.021***
	(0.008)	*(0.008)*	*(0.009)*	*(0.011)*
Mobile Money (MM_{it})			-0.015*	0.045***
			(0.008)	*(0.009)*
Controls (X_{it})	NO	YES	YES	YES
Constant	0.210***	0.195***	0.188***	10.15***
Household FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Obs	18,840	18,840	18,840	18,840
R-squared	0.120	0.145	0.152	0.310

4.4. Heterogeneity Analysis: Geography and Income

The aggregate results mask significant distributional heterogeneity. Table 4 dissects these effects by geography H3 and income strata H4.

Panel A (Geography): The interaction term $MM_{\{it\}}$* Rural is positive and significant (0.034). This implies that while urban households see a 6.2 percentage-point increase in savings, rural households see a 9.6 percentage-point increase. This confirms H_3: the marginal utility of DFS is highest where the physical infrastructure gap is widest. In remote areas, DFS is not just an improvement; it is a lifeline.

Panel B (Income - The "Debt Trap"): The interaction of Digital Credit with income quartiles reveals a regressive dynamic. For the wealthiest quartiles (Q3, Q4), digital credit strongly smooths consumption ($\beta \approx -0.060$). However, for the poorest quartile (Q1), the effect is statistically indistinguishable from zero (-0.005). This supports H4. For the ultra-poor, high-interest digital loans likely service existing distress rather than smoothing future consumption, neutralizing the resilience benefit.

Table 4: Heterogeneity Analysis (H3 & H4)

Variable	Coefficient	Std. Error
Mobile Money (MM_{it})	0.062***	(0.006)
($MM_{it} \times$ Rural Dummy)	**0.034** **	**(0.014)**
Controls / FE	YES	

Panel B: Interaction with Income Quartiles (H4)

Dependent Variable: Consumption Volatility

Variable	*Coefficient*	*Std. Error*
$DC_{it} \times$ Quartile 1 (Low)	*-0.005*	*(0.012)*
($DC_{it} \times$ Quartile 2)	*-0.032** *	*(0.011)*
($DC_{it} \times$ Quartile 3)	*-0.048*** *	*(0.010)*
($DC_{it} \times$ Quartile 4) (High)	*-0.060*** *	*(0.009)*
Controls / FE	YES	

4.5. Gender Heterogeneity and Mechanism Decomposition

To deepen our understanding of how these effects materialise, we examine gender dimensions and the substitution channels of financial flows. Gender Dynamics (Table 5): We find that Female-Headed Households (FHH) experience a significantly larger reduction in consumption volatility ($beta_{interaction}$= -0.033) than male-headed households. This provides empirical weight to the "privacy" hypothesis (Aker et al., 2016). Mobile money wallets are pin-protected, shielding female income from appropriation by kin or spouses. This control allows female heads to allocate resources more efficiently to smooth household consumption during shocks.

Mechanism Analysis (Table 6): How does Digital Credit smooth consumption? Table 6 reveals a substitution effect. Access to digital credit is negatively associated with Net Remittances (β = -0.085) and Internal Liquid Savings (β = -0.120).

- *Inference:* When a shock hits, households with credit access borrow instead of asking extended family for help (crowding out remittances) or depleting their own cash buffers (crowding out savings). While this smooths consumption in the short term, the depletion of savings and substitution with high-interest debt raises concerns about long-term financial health.

Table 5: Gender Heterogeneity Analysis

Variable	(1) Savings Depth	(2) Cons. Volatility
Mobile Money (MM_{it})	0.051***	-0.012
MM_{it} × Female Head (FHH_i)	0.028**	-0.033**
Female Head (FHH_i)	-0.015*	0.041***
Controls (X_{it})	YES	YES

Table 6: Mechanism Analysis - Remittances vs. Internal Savings

Dependent Variable:	(1) Net Remittances (Log)	(2) Internal Savings (Log)	(3) Consumption Volatility
Digital Credit (DC_{it})	-0.085**	-0.120***	-0.045**
Mobile Money (MM_{it})	0.245***	0.155***	-0.015
Controls	YES	YES	YES

4.6. Robustness: Instrumental Variables Strategy

To address potential endogeneity arising from unobserved time-varying factors that may jointly influence Mobile Money adoption and household savings, an instrumental variable (IV) strategy is employed. Adoption is instrumented using the interaction between GPS-based distance to the nearest mobile money agent and post-rollout timing. The IV estimates are comparable to, and slightly larger than, the baseline fixed-effects results, suggesting that attenuation bias may affect OLS estimates while alleviating concerns of reverse causality. First-stage diagnostics confirm strong instrument relevance, and over-identification tests provide no evidence against the exclusion restriction. Overall, the results support a causal interpretation of the positive effect of Mobile Money adoption on formal savings depth. Detailed results are reported in Appendix C.

4.7. Discussion of Findings

The above findings are that Digital financial tools through a number of distinct, constructive and non-substitutable a channel affects family balance sheet of households. Mobile Money mainly enhances households 'tangible wealth by turning informal cash into safe and traceable digital assets. This will lower the barriers to save money, make assets more controllable and lead toward a more stable replication of wealth, especially in rural areas where formal banking is not available for everyone during normal hours. Digital lending mostly goes through the liability side of household balance sheets. With digitised loans, citizens can use their disposable income from sources such as coal mining to replenish consumer credit even if one day he strikes gold and tops his wages. The authors probe the distribution of that income and follow families over time in order to see whether this stable situation reflects work-shaping or capital creation. For low-income households, digital credit often serves as a high-cost debt to replace informal insurance and savings, providing scant improvements in financial resilience while adding to future repayment risks. Gender differences further suggest that with Mobile Money, enhancing asset control has also brought household stability into being, especially among female-headed families. At all levels, then, digital finance is most effective in fostering financial resilience when it serves to lay the foundation for secure asset accumulation and not on short-term debt leverage alone.

5. Conclusion, Limitations, and Policy Implications

For this good governance measure, our purpose is to develop poor developing countries on two separate parts of the same Digital Financial Services (DFS) ecosystem are indeed systematically distinct but have distinct structures in terms of Mobile Money as infrastructure and digital lending as a decision-making tool. Using high-frequency longitudinal data with disjointed Difference-in-Differences identification strategy data sets generated by field work, we find that digital financial inclusion is not just generically good for people, as it is often claimed to be. There are in fact, great differences in balance sheets depending on the type of person. Evidence shows the adoption of Mobile Money formally increases savings depth by 6. 2 percentage points, with the strongest positive effects found among poor households in rural areas. Its implications for accounting and domestic financial strategy are profound: for example, digital payment rails can be considered a low-cost means to formalise the structure of a balance sheet. This type of transfer of mere cash into assets that are traceable sums of money is preservable. Mobile Money is thus a technology for accounting; it makes more secure what is owned by providing transparency and liquidity management at the household level. It also helps households to accumulate capital. By contrast, the effects of Digital Lending are more variegated and uneven in distribution. Where algorithmic credit undergoes expansion, the literature predicts reduced short-term consumption volatility, or even the smoothing out of that altogether. Yet such benefits are seen mainly among middle and higher-income households. For the poorest 25% of households, digital credit has little impact on their resilience at all and offers no relief from informal insurance or internal savings, with expensive debt replacing them. This has major accounting implications: digital credit restructures the liabilities side of a household's balance sheet but does not necessarily improve its net financial position. It raises questions about solvency and financial sustainability in the long run. Comparative analysis of savings-oriented digital financial instruments versus credit-oriented ones for households has so far been abstracted from all empirical evidence, or otherwise has existed with such little protraction value that it is not only very superficially researched as a subject. For the accounting profession, these findings stress that with the spread of new financial technologies come changes in asset-liability management, transitions from informal to formal finance, and, what's most importantly, the level rather than the quantity of financial inclusion. For both researchers and policy advocates, the distinction is very important if we are to design financial systems that promote sustainable inclusion rather than producing indebtedness.

5.1. Policy Implications

This divergence in our results implies that a change of our regulatory strategy must be toward less regulation, which is the laissez-faire policy, and toward increased regulation, which is the smart regulation policy, and we suggest a series of practical recommendations to central banks and other financial authorities. To begin with, the regulators will need to shift to bifurcated regulatory regimes, which implies that the DFS will no longer be treated as one. Since mobile Money has already demonstrated itself as a societal benefit in terms of spared money and resilience, it must be promoted with interoperability requirements and zero-rating of low transaction costs to achieve the greatest universality. On the other hand, stricter control over Digital Lending is necessary. The potentiality of a debt trap at the bottom of the pyramid is evidenced and, accordingly, dynamic debt-to-income (DTI) caps and regular reporting to credit reference bureaus are to be implemented to avoid numerous simultaneous loan takedowns on the various apps (CGAP, 2021). In order to mitigate the transparency issues in digital credit, regulators need to impose transparency in algorithms and standardised Truth in Lending disclosures. Due to the frictionless quality of digital loans, the actual cost of digital loans is frequently obscure, and, therefore, the regulators must mandate that apps display the Annual Percentage Rate (APR) of a loan prominently not only the daily or monthly charge prior to the execution of a loan. Moreover, central banks ought to audit algorithmic models of credit scoring to make sure they do not artificially discriminate against vulnerable groups or based on predatory behavioural biases, like encouraging loans at the end of the day. Since the advantages of resilience have been demonstrated in women, gender-centric financial design must be promoted by policy, especially in the digitalisation of Government-to-Person (G2P) social transfers. By issuing welfare funds to women as individual mobile funds instead of household heads, it is possible to take advantage of the privacy effect to increase child nutrition and family stability (Duflo, 2012). Lastly, access should be accompanied by capability by means of integrated digital literacy programs. Our results indicate that users with low incomes frequently tend to replace low social debt with costly digital debt. Additional features in these apps, like financial literacy programs, are to be integrated into the user interface (UI) of the app, such as just-in-time education modules that appear when a user tries to borrow and describe the overall cost of credit in easy terms (Carpena et al., 2017).

5.2. Limitations and Future Research

Although we have made a rigorous analysis, there are a number of limitations that should be recognised. To begin with, we are basing our data on self-reported financial diaries. As we winsorized outliers, self-reporting is prone to recall bias, especially the exact time when shocks to consumption occur. The results would be improved by combining administrative data with the telecom operator (Call Detail Records) so as to confirm the transaction volumes, but this would pose a serious privacy issue (Blumenstock, 2018). Second, the adoption phase is covered by the study period (2018-2023). It could be too brief to see the long-term balance consequences of digital credit. The debt trap hypothesis, H 4, takes a longer time horizon to find an answer on whether high frequency borrowing will cause eventual default and seizure of assets, or the borrowers will graduate into lower cost formal banking products. Third, our identification strategy takes advantage of the deployment of physical infrastructure (towers and agents). With a smartphone saturation rate turning to the point where it seems ubiquitous and satellite internet (e.g., Starlink) becoming available everywhere, the relationship between geography and access will become less close, and new instrumental variables will be required to infer causality in the future. The supply-side dynamics (in particular, the effect of the introduction of the Big Tech companies into the lending environment) on the competitive environment of the existing microfinance institutions (MFIs) should be the subject of future studies. Also, there can be experimental research on the effect of nudge interventions like SMS reminders to save or warnings on the accumulation of interest in order to provide low-cost policy instruments to reduce the behavioural risk factors found in this study (Thaler and Sunstein, 2008). Finally, the digital revolution is re-engineering the financial DNA of the developing economies. Although the mobile phone has managed to relocate the bank to the village, evidence based policy regime would be critical in ensuring that this relationship translates into prosperity and not precarity.

References

1. Aker, J. C., Boumnijel, R., McClelland, A., & Tierney, N. (2016). Payment Mechanisms and Anti-Poverty Programs: Evidence from a Mobile Money Cash Transfer Experiment in Niger. *Economic Development and Cultural Change*, 65(1), 1-37.
2. Allen, F., Demirgüç-Kunt, A., Klapper, L., & Martinez Peria, M. S. (2016). The Foundations of Financial Inclusion: Understanding Ownership and Use of Formal Accounts. *Journal of Financial Intermediation*, 27, 1-30.
3. Angrist, J. D., & Pischke, J. S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.
4. Ashraf, N., Karlan, D., & Yin, W. (2006). Tying Odysseus to the Mast: Evidence from a Commitment Savings Product in the Philippines. *The Quarterly Journal of Economics*, 121(2), 635-672.
5. Athey, S., & Imbens, G. W. (2017). The State of Applied Econometrics: Causality and Policy Evaluation. *Journal of Economic Perspectives*, 31(2), 3-32.
6. Banerjee, A. V., & Duflo, E. (2011). *Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty*. PublicAffairs.
7. Banerjee, A., Duflo, E., Glennerster, R., & Kinnan, C. (2015). The Miracle of Microfinance? Evidence from a Randomized Evaluation. *American Economic Journal: Applied Economics*, 7(1), 22-53.
8. Batista, C., & Vicente, P. C. (2020). Improving Access to Savings through Mobile Money: Experimental Evidence from African Smallholders. *Journal of Development Economics*, 143, 102414.
9. Beck, T., Demirgüç-Kunt, A., & Levine, R. (2007). Finance, Inequality and the Poor. *Journal of Economic Growth*, 12(1), 27-49.
10. Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? *The Quarterly Journal of Economics*, 119(1), 249-275.
11. Besley, T. (1995). Nonmarket Institutions for Credit and Risk Sharing in Low-Income Countries. *Journal of Economic Perspectives*, 9(3), 115-127.
12. Bharadwaj, P., Jack, W., & Suri, T. (2019). Fintech and Household Resilience to Shocks: Evidence from Digital Loans in Kenya. *Journal of Development Economics*, 140, 47-68.
13. Björkegren, D., & Grissen, D. (2020). The Potential of Digital Credit to Bank the Poor. *American Economic Review: Insights*, 2(1), 93-106.
14. Blechman, J. (2016). *Mobile Credit in Kenya: The Privacy-Profit Trade-off*. The Berkman Klein Center for Internet & Society at Harvard University.
15. Blumenstock, J. E. (2018). Don't Forget People in the Use of Big Data for Development. *Nature*, 561(7722), 170-172.
16. Blumenstock, J., Callen, M., & Ghani, T. (2015). Promises and Pitfalls of Mobile Money in Afghanistan: Evidence from a Randomized Control Trial. *The Proceedings of the ICTD 2015*.
17. Bruhn, M., & Love, I. (2014). The Real Impact of Improved Access to Finance: Evidence from Mexico. *Journal of Finance*, 69(3), 1347-1376.
18. Burgess, R., & Pande, R. (2005). Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment. *American Economic Review*, 95(3), 780-795.
19. Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics*, 225(2), 200-230.
20. Carpena, F., Cole, S., Shapiro, J., & Zia, B. (2017). Unpacking the Causal Chain of Financial Literacy. *World Bank Economic Review*, 33(2), 1-37.

21. CGAP. (2021). *Consumer Protection in Digital Finance: A Review of the Evidence*. Consultative Group to Assist the Poor, Washington, D.C.
22. Collins, D., Morduch, J., Rutherford, S., & Ruthven, O. (2009). *Portfolios of the Poor: How the World's Poor Live on $2 a Day*. Princeton University Press.
23. Crépon, B., Devoto, F., Duflo, E., & Pariente, W. (2015). Estimating the Impact of Microcredit on Those Who Take It Up: Evidence from a Randomized Experiment in Morocco. *American Economic Journal: Applied Economics*, 7(1), 123-150.
24. Deaton, A. (1991). Saving and Liquidity Constraints. *Econometrica*, 59(5), 1221-1248.
25. Deaton, A. (1997). *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. World Bank Publications.
26. Demirgüç-Kunt, A., & Klapper, L. (2013). Measuring Financial Inclusion: Explaining Variation Across and Within Countries. *Brookings Papers on Economic Activity*, 2013(1), 279-340.
27. Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2018). *The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution*. World Bank.
28. Diamond, D. W. (1984). Financial Intermediation and Delegated Monitoring. *The Review of Economic Studies*, 51(3), 393-414.
29. Donovan, K. (2012). Mobile Money for Financial Inclusion. In *Information and Communication for Development* (pp. 61-73). World Bank.
30. Duflo, E. (2012). Women Empowerment and Economic Development. *Journal of Economic Literature*, 50(4), 1051-1079.
31. Duncombe, R., & Boateng, R. (2009). Mobile Phones and Financial Services in Developing Countries: A Review of Concepts, Methods, Issues, Evidence and Future Directions. *Third World Quarterly*, 30(7), 1237-1258.
32. 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.
33. Francis, E., Blumenstock, J., & Robinson, J. (2017). *Digital Credit: A Snapshot of the Current Landscape and Open Research Questions*. CEGA White Paper.
34. Friedman, M. (1957). *A Theory of the Consumption Function*. Princeton University Press.
35. Giné, X., & Mansuri, G. (2011). Money or Ideas? A Field Experiment on Constraints to Entrepreneurship in Rural Pakistan. *World Bank Policy Research Working Paper*.
36. Goodman-Bacon, A. (2021). Difference-in-Differences with Variation in Treatment Timing. *Journal of Econometrics*, 225(2), 254-277.
37. Grossman, J., & Tarazi, M. (2014). Serving Smallholder Farmers: Recent Developments in Digital Finance. *CGAP Focus Note*, 94.
38. Higgins, D., Kendall, J., & Lyon, B. (2012). Mobile Money Usage Patterns of Kenyan Small and Medium Enterprises. *Innovations: Technology, Governance, Globalization*, 7(2), 67-81.
39. Ivatury, G., & Mas, I. (2008). The Early Experience with Branchless Banking. *CGAP Focus Note*, 46.
40. Jack, W., & Suri, T. (2014). Risk Sharing and Transaction Costs: Evidence from Kenya's Mobile Money Revolution. *American Economic Review*, 104(1), 183-223.
41. Karlan, D., & Morduch, J. (2010). Access to Finance. In *Handbook of Development Economics* (Vol. 5, pp. 4703-4784). Elsevier.
42. Karlan, D., & Zinman, J. (2010). Expanding Credit Access: Using Randomized Supply Decisions to Estimate the Impacts. *Review of Financial Studies*, 23(1), 433-464.
43. Klapper, L., El-Zoghbi, M., & Hess, J. (2016). Achieving the Sustainable Development Goals: The Role of Financial Inclusion. *CGAP Working Paper*.
44. Ky, S., Rugemintwari, C., & Sauviat, A. (2018). Does Mobile Money Affect Saving Behavior? Evidence from a Developing Country. *Journal of African Economies*, 27(3), 285-320.
45. Levine, R. (2005). Finance and Growth: Theory and Evidence. *Handbook of Economic Growth*, 1, 865-934.
46. Mas, I., & Morawczynski, O. (2009). Designing Mobile Money Services Lessons from M-PESA. *Innovations: Technology, Governance, Globalization*, 4(2), 77-91.
47. Mas, I., & Radcliffe, D. (2010). Mobile Payments Go Viral: M-PESA in Kenya. *Journal of Financial Transformation*, 32, 169-182.
48. Mbiti, I., & Weil, D. N. (2011). Mobile Banking: The Impact of M-Pesa in Kenya. *National Bureau of Economic Research Working Paper Series*, No. 17129.
49. Mbiti, I., & Weil, D. N. (2016). Mobile Banking: The Impact of M-Pesa in Kenya. In *African Successes, Volume III: Modernization and Development* (pp. 247-293). University of Chicago Press.
50. McKenzie, D., & Woodruff, C. (2008). Experimental Evidence on Returns to Capital and Access to Finance in Mexico. *World Bank Economic Review*, 22(3), 457-482.
51. Mora-Rivera, J., & Garcia-Mora, F. (2021). Internet Access and Poverty Reduction: Evidence from Rural and Urban Mexico. *Telecommunications Policy*, 45(2), 102076.
52. Morawczynski, O. (2009). Exploring the Usage and Impact of "Transformational" Mobile Financial Services: The Case of M-PESA in Kenya. *Journal of Eastern African Studies*, 3(3), 509-525.
53. Morduch, J. (1999). The Microfinance Promise. *Journal of Economic Literature*, 37(4), 1569-1614.
54. Mullainathan, S., & Shafir, E. (2013). *Scarcity: Why Having Too Little Means So Much*. Times Books.
55. Munyegera, G. K., & Matsumoto, T. (2016). Mobile Money, Remittances, and Household Welfare: Panel Evidence from Rural Uganda. *World Development*, 79, 127-137.
56. Plyler, M. G., Haas, S., & Nagarajan, G. (2010). *Community-Level Economic Effects of M-PESA in Kenya*. Financial Services Assessment.
57. Riley, E. (2018). Mobile Money and Risk Sharing Against Village Shocks. *Journal of Development Economics*, 135, 43-58.
58. Roodman, D. (2012). *Due Diligence: An Impertinent Inquiry into Microfinance*. Center for Global Development.
59. Rutherford, S. (2000). *The Poor and Their Money*. Oxford University Press.
60. Schumpeter, J. A. (1911). *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*. Harvard University Press.
61. Stiglitz, J. E., & Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *The American Economic Review*, 71(3), 393-410.
62. Suri, T. (2017). Mobile Money. *Annual Review of Economics*, 9, 497-520.
63. Suri, T., & Jack, W. (2016). The Long-Run Poverty and Gender Impacts of Mobile Money. *Science*, 354(6317), 1288-1292.

64. Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving Decisions About Health, Wealth, and Happiness*. Yale University Press.
65. Townsend, R. M. (1994). Risk and Insurance in Village India. *Econometrica*, 62(3), 539-591.
66. World Bank. (2021). *The Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19*. Washington, DC: World Bank.
67. Zinman, J. (2014). Consumer Credit: Too Much or Too Little (or Just Right)? *Annual Review of Economics*, 6, 251-278.

Appendices

Appendix A: Correlation Matrix of Key Variables

Table A1 reports the pairwise correlation coefficients for the main regression variables. The highest observed correlation is between Education and Income (0.45), suggesting no severe multicollinearity issues. Variance Inflation Factors (VIF) for all variables remain below 2.1.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Formal Savings Depth	1.00							
(2) Cons. Volatility	-0.32	1.00						
(3) Mobile Money (MM_{it})	0.41	-0.15	1.00					
(4) Digital Credit (DC_{it})	0.12	-0.28	0.24	1.00				
(5) Age (Head)	-0.18	0.05	-0.22	-0.08	1.00			
(6) Education (Years)	0.35	-0.12	0.31	0.15	-0.25	1.00		
(7) Log Income	0.48	-0.21	0.38	0.19	-0.10	0.45	1.00	
(8) Rural Dummy	-0.22	0.14	-0.18	-0.09	0.08	-0.33	-0.41	1.00

Appendix B: Detailed Variable Definitions

Variable	Definition	Data Source
Dependent Variables		
Formal Savings Depth (S_{it})	The total value of liquid assets held in formal accounts (bank, SACCO, mobile wallet) divided by total monthly household income. Capped at 100%.	Fin. Diaries
Consumption Volatility (CV_{it})	The coefficient of variation (Standard Deviation / Mean) of per capita food expenditure calculated over the trailing 6-month window.	Fin. Diaries
Log Consumption (C_{it})	Natural logarithm of real monthly per capita consumption expenditure, spatially deflated using regional price indices.	Survey
Treatment Variables		
Mobile Money (MM_{it})	Dummy = 1 if any household member conducted at least one cash-in, cash-out, or P2P transfer using an agent in the past 30 days; 0 otherwise.	Survey
Digital Credit (DC_{it})	Dummy = 1 if the household successfully accessed and utilized a digital micro-loan (e.g., M-Shwari, Tala, Branch) in the reference period; 0 otherwise.	Survey
Control Variables		
Asset Shock	Dummy = 1 if household reported loss of livestock, crop failure, or theft of assets > 10% of annual income in the past year.	Survey
Distance to Agent	Euclidean distance (km) from the household GPS coordinates to the nearest active mobile money agent.	GIS / Admin
Off-Farm Employment	Dummy = 1 if the primary income source is not agriculture (e.g., wage labor, small business).	Survey

Appendix C: Event Study Estimates

*Table A2 presents the coefficients plotted in the Event Study (Figure 2). Time **t**=0 is the year of adoption. The omitted category is **t**=-1.*

Time to Adoption	Coeff. (Savings)	Std. Err.	Coeff. (Volatility)	Std. Err.
$t = -3$	0.004	(0.006)	-0.002	(0.008)
$t = -2$	-0.002	(0.005)	0.001	(0.007)
$t = -1$	*(Reference)*	-	*(Reference)*	-
$t = 0$ (Adoption)	**0.045***	(0.006)	**-0.028**	(0.009)
$t = +1$	**0.061***	(0.007)	**-0.042***	(0.009)
$t = +2$	**0.068***	(0.008)	**-0.048***	(0.010)
$t = +3$	**0.072***	(0.009)	**-0.051***	(0.011)

Note: Non-significant coefficients for t < 0 indicate parallel pre-trends.

Table A3: Robustness Check - Instrumental Variable (IV) Estimation

2SLS Estimates instrumenting Adoption with Distance to Agent × Post-Rollout

	First Stage	***Second Stage (2SLS)***
Dependent Variable:	*MM Adoption (MM_{it})*	*Formal Savings Depth*
IV: Distance × Post	***-0.145****	
IV: Distance × Post		***0.074****
F-Statistic (Weak ID)	*42.5*	
Hansen J (Overid.)	-	*0.34 (p=0.56)*

Appendix D: Placebo Test Distribution

To verify that our results are not driven by spurious correlation, we conducted a placebo test by randomly assigning the "Mobile Money Adoption" date to households 1,000 times.

- **Mean Placebo Coefficient:** 0.0004
- **Standard Deviation:** 0.012
- **95th Percentile:** 0.024
- **Actual Estimated Effect:** 0.062 (Far exceeds the 95th percentile threshold)