The Impact of Digital Financial Services on Rural Farming Households' Welfare in Northwestern Nigeria

Enahoro Innocent Ojiri[a], David Morphy[b], Takshil Sachdev[c], Khadijat Amolegbe[a], Vageesha Bainwala[e], and Sunmibola Olaniyi[a]

[a]Department of Agricultural Economics, University of Ilorin

[b]Economics Department, Colgate University

[c]Department of Economics, Cornell University

[d]Department of Economics, Northwestern University

June, 2026

1 Abstract

This Pre-Analysis Plan outlines the analytical framework for a cluster-randomized field experiment examining the impact of Digital Financial Services (DFS) on household welfare. The study targets heads of farming households aged 18 years and above who possess a valid phone number and a functional mobile phone, including basic phones, feature phones, and smartphones. Participants are randomly assigned to either the treatment group or the control group. The research team partners with OPay, a leading Nigerian fintech company, to design and implement the intervention. This analysis plan presents the study design, outcome measures, and econometric approaches that guide the analysis.

2 Motivation

Over the past decade, the rapid expansion of digital financial services (DFS) has fundamentally reshaped the financial landscape of developing economies (Mpofu and Mhlanga, 2022; Sharma and Diaz Andrade, 2023). By leveraging mobile technology, DFS has lowered transaction costs, reduced geographical barriers, and expanded access to formal financial systems for previously excluded populations (Geach, 2007; Yakubu, Saani, and Enchill, 2025). This transformation has been particularly pronounced in Sub-Saharan Africa, where mobile money platforms have emerged as a dominant channel for financial inclusion. DFS is often positioned as a critical tool for enhancing savings behavior, improving household welfare, and fostering economic resilience (David-West and Nwagwu, 2018; Aker and Carroll, 2022).

Sub-Saharan Africa (SSA) has experienced substantial growth in mobile phone penetration, creating an enabling environment for DFS expansion (Kouladoum, Wirajing, and Nchofoung, 2022). The region now accounts for a significant share of global mobile money usage, with services such as M-Pesa in Kenya, MTN MoMo in Ghana, and OPay in Nigeria driving financial access for millions of previously unbanked individuals. The diffusion of mobile-enabled financial services has reshaped the financial landscape, particularly in areas where traditional banking infrastructure remains limited (Mpofu and Mhlanga, 2022; Sharma and Diaz Andrade, 2023). The region now accounts for a significant share of global mobile money usage, with services such as M-Pesa in Kenya, MTN MoMo in Ghana, and OPay in Nigeria driving financial access for millions of previously unbanked individuals. The diffusion of mobile-enabled financial services has reshaped the financial landscape, particularly in areas where traditional banking infrastructure remains limited.

Despite Nigeria's position as a leading hub for Digital Financial Services (DFS) in Sub-Saharan Africa, with a rapidly growing fintech sector and increasing digital transaction volumes, financial exclusion remains substantial (Siano et al., 2020). Approximately 36% of adult Nigerians are still financially excluded, highlighting a persistent gap between access and use. This disparity is even more pronounced in rural areas, where about 37% of the population is excluded from the financial ecosystem, compared to 17% in urban areas (EFInA, 2024).

Early experimental evidence strongly suggests that DFS is welfare-enhancing. For instance, Dupas and Robinson (2013) show that reducing access barriers through simple savings accounts significantly increased savings among micro-entrepreneurs in Kenya, particularly women. This finding suggests that financial exclusion is largely driven by structural constraints rather than a lack of willingness to save. In this sense, DFS, by easing access and lowering costs, should theoretically lead to higher savings accumulation.

However, subsequent evidence has presented a more nuanced and, at times, contradictory picture. Using large-scale quasi-experimental data, Suri and Jack (2016) find that mobile money significantly improves household welfare, primarily by facilitating risk-sharing and consumption smoothing. Yet, these gains do not necessarily translate into sustained increases in savings balances. Instead, mobile money functions as an alternative to precautionary savings by enabling faster access to informal insurance networks. This raises an important conceptual shift: DFS may transform how households manage risk rather than directly increasing their savings. While this suggests that mobile money can enhance household welfare by strengthening informal insurance networks, it also reveals a limitation: DFS alone does not reliably build savings buffers. This distinction motivates the present intervention, which is designed not to replace risk-sharing mechanisms but to complement them by encouraging the conversion of liquidity access into durable savings behaviour.

Nigeria presents a particularly relevant context for examining rural financial exclusion and the role of DFS. Despite being the largest economy in Africa and home to Africa's rapidly expanding digital financial sector, access to and use of formal financial services remain uneven across regions (Adeleke and Alabede, 2022). Rural areas, particularly in Northwestern Nigeria, are characterized by high poverty levels, a strong reliance on subsistence agriculture, inadequate infrastructure, and relatively low educational attainment. These factors collectively constrain the adoption and effective use of Digital Financial Services (DFS). Most farmers in the region rely on basic or feature phones, largely due to income constraints and the practical demands of agricultural livelihoods. Low levels of literacy and formal education further limit their ability to navigate and utilize digital financial applications. In addition, the limited presence of formal banking institutions and inadequate telecommunications infrastructure, including poor network coverage, hinder access to and the effective utilization of DFS in these rural communities (Adeleke and Alabede, 2022).

3 Research Questions

Guided by the broad objective of the study, which is to evaluate the impact of Digital Financial Services on the welfare of rural farming households in Northwestern Nigeria, this study addresses the following research question:

- What is the impact of DFSs on savings and welfare (asset ownership and food security) of rural farming households?
- What are the mechanisms through which DFS influences households' welfare outcomes?

4 Research Strategy

4.1 Sampling

4.1.1 Sampling frame

This study was conducted in rural communities in Northwestern Nigeria, specifically in Jigawa and Kano states. These states share strong socioeconomic and historical similarities. Prior to 1991, they constituted a single administrative unit; after many years of formal separation, they are still referred to as the Kano region. The region is characterized by high poverty levels, low financial inclusion rates, and a predominantly subsistence-agriculture-based population. For this study, the eligible population is farming households, but we have eligibility criteria at both the community and household levels. The communities are farming communities and have strong network connectivity. The enumerators ask whether the main activity of this community is farming, and whether they can make calls, receive, and send SMS. The household heads are randomly drawn from a list of farmers in the community, and to retain them in the sample, we further ask whether they have a valid mobile number and a functioning mobile phone (basic, feature, or smartphone).

4.1.2 Statistical Power

The sample size for this cluster-Randomized Controlled Trial (cRCT) was determined a priori using data from the 2023 EFInA Access to Finance Survey. For this study, we assumed a minimum detectable effect (MDE) of ₦60,000 in household savings over the last 6 months, corresponding to approximately 0.40 standard deviations, a statistical power of 80%, a significance level of 5%, and an Intra-Cluster Correlation coefficient (ICC) of 0.047, the results from the power calculation indicated that a minimum of 22 clusters (11 treatment and 11 control communities) with at least 15 households per cluster is required to obtain the MDE. Given the limited sample size, the study is adequately powered to detect moderate-to-large treatment effects. Consequently, smaller effects may not be estimated with sufficient precision and may be statistically indistinguishable from zero. Accordingly, the study includes 24 communities, 12 assigned to each arm, and 216 households per arm, resulting in a cluster size of 18 households per community and a total sample size of 432. The additional communities and households we added served as a buffer in situations where we have a community crisis, where the team could not have access to the community, or in a situation where the household decides not to be involved in the survey or decides to leave the community.

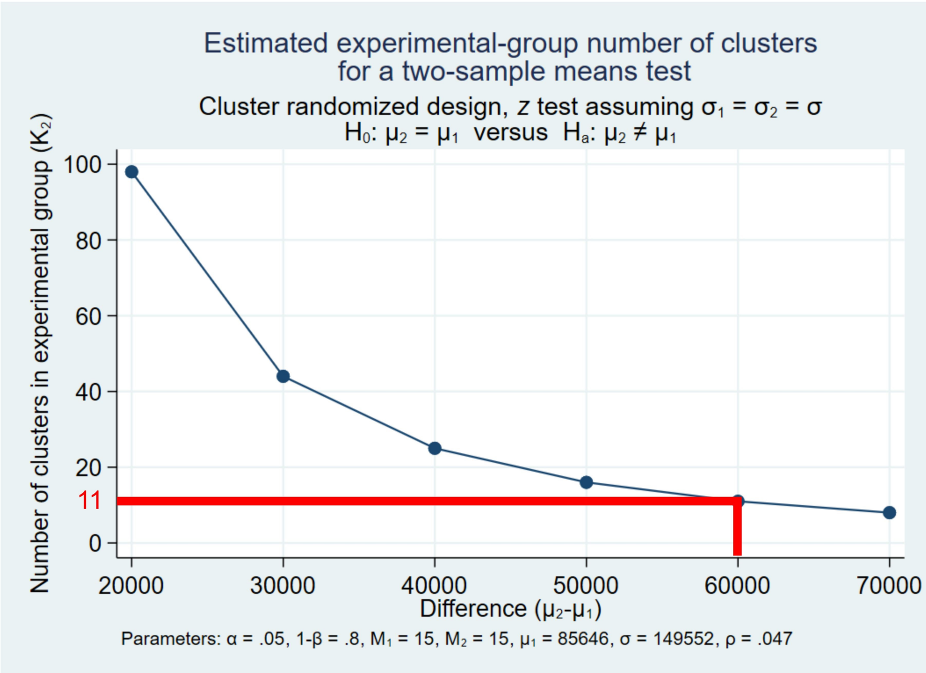

Figure 1: Power calculation for the DFS-Rural Savings project

4.2 Assignment to Treatment

This study randomly assigned communities to either the treatment or control group, with randomization conducted at the community level. The household head was the unit of analysis. Stata was used for both the randomization process and basic data analysis, including balance tests. The intervention consisted of a bundled package that included training on the use of Digital Financial Services (DFS), training manuals in both English and Hausa, free account opening, and an ATM card. The training was delivered in a single session lasting approximately eight hours. Participants received instruction on a range of DFS-related modules, including an introduction to DFS, practical use of DFS platforms, digital security and fraud prevention, case studies using Opay, sending and receiving money, cash withdrawals through Point-of-Sale (POS) agents, savings on Opay, the use of savings goals, balance checks, complaint and redress mechanisms, and role-play exercises designed to reinforce learning and enhance participant engagement. To reduce financial barriers to DFS usage, the research team provided the treatment group with a free account, for which agent fees would otherwise have been charged, as well as a free ATM card. Participants in the control group did not receive any component of the bundled intervention. However, both the treatment and control groups received detergent as compensation for the time spent participating in data collection activities. The training manual was jointly developed by the research team, Opay, and staff from Innovation for Poverty Action (IPA) Nigeria, who were involved in the project. Field trainers were carefully selected based on their prior experience and demonstrated performance in delivering similar training programs. Selected trainers underwent an intensive three-day training program conducted by the research team. In addition, several rounds of pilot testing of the training manual were conducted in pilot communities to refine both the training content and delivery approach. Following the training and piloting exercises, only trainers who successfully met the required performance standards were selected to deliver the intervention to participants in the treatment group.

4.3 Attrition from the Sample

The power calculations indicated a required sample of 11 communities per study arm (treatment and control), with 15 households sampled in each community. To mitigate the potential effects of attrition and preserve statistical power, the study oversampled by including two additional communities and three additional households per community prior to the community and household identification survey. This precautionary measure was intended to ensure that the final sample and cluster sizes remained above the minimum thresholds required by the power calculations in the event of community-level disruptions, such as conflicts or communal clashes, as well as household-level attrition resulting from migration or relocation. Another measure to ensure that attrition remains below the bar, this study collected the household's geolocation for easy directions, and the mobile number of a neighbor who should know where they travel to or relocate to during the communities and households identification. All this information allows us to keep the attrition rate below 5% to ensure a powered study.

4.4 Fieldwork

4.4.1 Instruments

This study employed primary data collected through a CAPI developed using KoboToolbox. We received the ethical letter from the University of Ilorin confirming that the survey instruments complied with the ethical procedures. We focus on many sections such as consent and basic household information, socioeconomic characteristics, mobile phone ownership, access to and use of bank and fintech, labour market participation, digital financial services, savings, payment, remittances, credit, informal savings, food security, crop production information, and access to infrastructure.

4.4.2 Data Collection

This study collected data at different points, from community and household identification through the baseline to the endline. This study started with the identification of communities and households. The team identified farming communities in the states and farming households in each community from 10 to 28 January 2025. The baseline survey was run from 28 February to 10 March 2025. The research team randomly assigned communities to the control and treatment groups. 10 months after the intervention, we collected the endline data from 28 February to 10 March 2026. The data collected will be available only to the research team, and in some circumstances where we must share it, the research team will share only the deidentified dataset.

4.4.3 Data Processing

We processed the data we collected from the community and household identification and preloaded them into the survey instruments for the baseline and endline data collection. At baseline, the data were used to run the randomization and balance tests to ensure that the control and treatment groups are comparable. We will clean and analyze the baseline and endline to produce the graphs, figures, tables, and results of this study. Data for the baseline and endline were collected prior to completion of this Pre-Analysis Plan, but they have not yet been analyzed. Data cleaning and analysis will begin after the Pre-Analysis Plan is uploaded to the AEA RCT registry. To ensure confidentiality, the team has been working on this project and ensuring that any data used in the reproducible package is de-identified and ready for public upload. We ensure the respondent's identity is kept strictly confidential and will be used only by the research team, not made available to the general public.

5 Empirical Analysis

5.1 Variables

The variables of interest in the study were selected from the questionnaire's different sections, including socioeconomic characteristics, Labour participation, Asset ownership, digital knowledge, Digital financial services, Informal saving activities, food insecurity, and crop production information.

Table 1: Description of selected variables

Variable	Description
Years of Education	The highest level of education attained by the household head.
Labour Force Participation	The amount of money earned from labour activities.
Labour Earnings	The method through which the respondent receives payment for labour services rendered (transfer, mobile money, or bank payment).
Worked > 20 Hours per Week	Working as a labourer for more than 20 hours per week.
Household Asset Index	All assets owned by the household head, including durable, productive, agricultural, housing, land, and livestock assets.
Ownership of Formal ID	Possession of a formal means of identification, such as a National Identification Number (NIN), National ID card, passport, or Bank Verification Number (BVN).
Mobile Phone Type	The type of mobile phone used by the household head (basic phone, feature phone, or smartphone).
Savings Amount	The amount of money saved through a digital savings platform during the last six months.
Payment Activity	The average amount of money sent and received through digital payment platforms.
Remittance Activity	The average total amount of money received from friends and family, both domestically and internationally.
Access to Credit	The average total amount of money received as loans through fintech platforms or banks.
Food Security Index	The food security status of the household.
Internet Expenditure	Average monthly expenditure on internet services (₦).
Airtime Expenditure	Average monthly expenditure on airtime (₦).
Value of Crop Production	The monetary value (₦) of crops harvested from the respondent's farming activities.

6 Balancing Checks

We have run some basic balance tests immediately after the baseline study to ensure that the treatment and the control groups are comparable. This study employed T-test and Ordinary Least Squares (OLS) on a set of variables, and primarily on the outcome variables, including savings, credit, payment frequency, amount of informal savings in the last six months, asset ownership, and food security status. We will also check the balance across attritors and non-attritors using logit regression, with the outcome a binary indicator of attrition, and we will run it with the treatment variable and the other variables of interest. Although we have put some forensic measures in place to keep the attrition percentage below 5%, including GPS coordinates, the phone numbers of family members, and immediate neighbors who know the way around the household. That is to say, the neighbor knows where they relocated to and can still have their mobile number in case we consider phone surveys.

Table 2: Baseline Characteristics of Study Participants

Variable	All Mean	Control Mean	Treatment Mean	P-value
	(1)	(2)	(3)	(4)
Age of household head (years)	45.44	45.12	45.75	0.59
Married (%)	96	97	96	0.59
Male-headed household (%)	99	99	99	0.98
Household size	11.77	11.84	11.70	0.81
Completed post-secondary education (%)	42	45	39	0.18
Agriculture as primary activity (%)	91	94	88	0.06*
Total farm size (ha)	2.35	2.32	2.39	0.69
Value of durable assets (₦)	1,221,066	1,803,122	644,302	0.31
Own an ATM card (%)	94	92	94	0.60
Own a savings account (%)	87	85	88	0.51
Savings (₦)	137,585	163,147	112,255	0.10
Total informal savings (₦)	93,296	81,455	103,257	0.36
Payments made (₦)	28,129	25,509	30,725	0.44
Amount received (₦)	128,105	130,827	125,358	0.90
Remittances (₦)	22,306	19,550	25,087	0.54
Observations	438	220	218	

Notes: Column (1) reports the sample mean for all households. Columns (2) and (3) report means for the control and treatment groups, respectively. Column (4) reports the p-value from a test of equality of means between treatment and control groups. * indicates significance at the 10% level.

7 Outcome variables

This study examines two primary outcome variables. The first relates to household savings behaviour. To capture both the extensive and intensive margins of savings, we consider (i) a binary indicator equal to one if the household head reported any positive savings during the previous six months and zero otherwise, and (ii) the total amount of savings accumulated by the household head over the same period. The second primary outcome is a composite welfare index constructed from measures of household asset ownership and the Household Food Insecurity Access Scale (HFIAS). The Asset ownership variable will be transformed using Principal Component Analysis (PCA) into an asset index, which will then be standardized. The HFIAS variable will be reverse-coded to align with asset ownership, with higher asset ownership translating to higher welfare, and will later be standardized. To standardize the two variables, we will use the following formula.

$$Z_i = \frac{x_i - \bar{x}}{s} \tag{1}$$

Where:

Z_i represent the standardized food security status or the asset index, x_i' is the value of the variable for household i, $\bar{x}$ is the mean, and s is the standard deviation.

To build the composite welfare index, we use the formula below:

$$WelfareIndex_i = \frac{z(asseIndex) + z(FoodSecurity)}{2} \tag{2}$$

Where:

$WelfareIndex_i$ represent the composite welfare index, z(asseIndex) is the standardized asset index, and z(FoodSecurity) is the standardized food security.

8 Treatment Effects

To estimate the impact of Digital Financial Services (DFS) on key outcomes, including savings, household assets, and household food security, we will employ the Analysis of Covariance (ANCOVA) estimator. ANCOVA is widely regarded as the preferred method for analysing randomized controlled trials (RCTs) with both baseline and endline measurements. As noted by Vickers (2001), ANCOVA improves statistical efficiency by controlling for baseline values of the outcome variable, thereby accounting for any residual baseline imbalances between treatment groups. In addition, it generally provides more precise treatment effect estimates, increases statistical power, and facilitates the estimation of confidence intervals and significance tests for treatment effects. We will estimate the intent to treat and the treatment on the treated via ANCOVA. The model specifications for running both the intent-to-treat (ITT) and the treatment-on-the-treated (TOT) analyses under imperfect compliance, using ANCOVA are specified below:

8.1 Intent to treat (ITT)

$$Y_i, t = \alpha + \beta T_i + \gamma Y_{i,0} + \varepsilon_i \tag{3}$$

Where:

Y_i, t represents the outcome variables at the endline, $Y_{i,0}$ are the baseline outcomes, T_i represent the treatment variable for 1 if assigned to treatment, and 0 if assigned to the control group, β is the ITT estimate.

8.2 Treatment on the treated

It estimates the effect of DFS on those who actually receive the treatment. The actual take-up rate is endogenous (compliers may differ from non-compliers), so we need an instrumental variable (IV) using T_i the assignment variable as the instrument for Di the actual receipt. The actual take-up rate is defined as the proportion of participants who complete the full intervention package. Specifically, a participant is considered to have taken up the intervention if they attended the eight-hour training session, received the training manual, opened an OPay account (for new users), and received an OPay ATM card (for either new users or existing OPay users who did not previously possess an ATM card).

We will be using Two-Stage Least Squares (2SLS) with ANCOVA controls

First Stage

$$D_i = \pi + \pi_1 T_i + \lambda Y_{1i,0} + v_i \tag{4}$$

Second Stage

$$Y_{i,t} = \alpha + \hat{D} + \gamma Y_{i,0} + \varepsilon_i \tag{5}$$

Where: $Y_{i,t}$ represents the endline outcomes (savings and the welfare index), $Y_{i,0}$ are the baseline outcome variables, $_i$ is the predicted take-up from the first stage regression, γ is the TOT (LATE) estimate.

9 Heterogeneous Effects

To estimate the effects of DFS across phone type ownership (basic phone, feature phone, and smartphone), we will employ Analysis of Heterogeneous Effects with Covariate Adjustment (ANHECOVA). Compared with conventional ANCOVA, ANHECOVA allows for treatment effect heterogeneity by incorporating interactions between treatment assignment and baseline covariates. Under random assignment, this approach yields consistent estimates of the average treatment effect and can improve statistical efficiency relative to standard ANCOVA, particularly when treatment effects vary across individuals (Lin, 2013; Negi and Wooldridge, 2021). It relaxes the assumption that the covariate slopes at baseline are equal across the control and treatment groups. The moderator M_i (phone type) we will use in this model has been specified relative to the baseline.

The specialized form for the ITT is as follows:

$$Y_{i,t} = \alpha + \beta_1 T_i + \beta_2 M_i + \gamma_1 (T_i * Y_{i,0}) + \gamma_2 (T_i * M_i) + \varepsilon_i \tag{6}$$

Where:

$Y_{i,t}$ represent the endline outcome variables, $Y_{i,0}$ are the baseline outcome variables, M_i is the moderator variable, which is a three-level categorical set of dummy variables representing basic, feature, and smartphones. γ_2 estimates the heterogeneous ITT effect across all the control variables that interact with the treatment variable.

10 TOT Heterogeneity using ANHECOVA and IV

Under imperfect compliance, we will run a treatment on the treated analysis using ANHECOVA and an Instrumental variable D_i.

The first stage is as follows:

$$D_i = \pi_0 + \pi_1 T_i + \pi_2 Y_{i,0} + \pi_3 M_i + \pi_3 (T_i * Y_{i,0}) + \pi_5 (T_i * M_i) + \upsilon_i \tag{7}$$

Second stage

$$Y_{i,t} = \beta_0 + \beta_1 \hat{D}_i + \beta_3 Y_{i,0} + \beta_4 M_i + \beta_5 (\hat{D}_i * Y_{i,0}) + \beta_6 (\hat{D}_i * M_i) + \varepsilon_i \tag{8}$$

Where:

$Y_{i,t}$ represent the endline outcome variables, $Y_{i,0}$ are the baseline outcome variables, M_i is the moderator variable, which is a three-level categorical set of dummy variables representing basic, feature, and smartphones. β_1 estimates the heterogeneous TOT/LATE effect across Mi, using instrument D_i ,$D_i * Y_{i,0}$, $D_i * M_i$ measures TOT/LATE effect across all the control variables, which are interacted with the treatment variable.

11 Standard Error Adjustments

Given the clustered nature of the randomized controlled trial, standard errors will be adjusted to account for intra-cluster correlation. Since treatment assignment occurs at the community level, observations within the same community may be correlated, violating the independence assumption of ordinary least squares estimation. To address this, all regressions will employ cluster-robust standard errors at the randomization level.

12 Preanalysis Plan Note

Survey work was completed on 10 March 2026. This analysis plan is being filed after data has been collected, but before any analysis has been conducted aside from basic balance and attrition checks.

References

Adeleke, Richard and Opeyemi Alabede (2022). “Understanding the patterns and correlates of financial inclusion in Nigeria”. In: *GeoJournal* 87.3, pp. 2405–2422.

Aker, Jenny and David A Carroll (2022). “The state of digital financial services in francophone West Africa”. PhD thesis. Ferdi.

David-West, Olayinka and Ijeoma Nwagwu (2018). “SDGs and digital financial services (DFS) entrepreneurship: challenges and opportunities in Africa’s largest economy”. In.

Dupas, Pascaline and Jonathan Robinson (2013). “Savings constraints and microenterprise development: Evidence from a field experiment in Kenya”. In: *American Economic Journal: Applied Economics* 5.1, pp. 163–192.

EFInA (2024). “Access to financial services in Nigeria 2024 survey.” In: URL: https://www.efina.org.ng/publications/access-to-financial-services-in-nigeria-2024-%20survey.

Geach, Neal (2007). “The digital divide, financial exclusion and mobile phone technology: Two problems, one solution?” In: *Journal of International Trade Law and Policy* 6.1, pp. 21–29.

Kouladoum, Jean-Claude, Muhamadu Awal Kindzeka Wirajing, and Tii N Nchofoung (2022). “Digital technologies and financial inclusion in Sub-Saharan Africa”. In: *Telecommunications Policy* 46.9, p. 102387.

Lin, Winston (2013). “Agnostic notes on regression adjustments to experimental data: Reexamining Freedman’s critique”. In: *The Annals of Applied Statistics*, pp. 295–318.

Mpofu, Favourate Y and David Mhlanga (2022). “Digital financial inclusion, digital financial services tax and financial inclusion in the fourth industrial revolution era in Africa”. In: *Economies* 10.8, p. 184.

Negi, Akanksha and Jeffrey M Wooldridge (2021). “Revisiting regression adjustment in experiments with heterogeneous treatment effects”. In: *Econometric Reviews* 40.5, pp. 504–534.

Sharma, Himanshu and Antonio Diaz Andrade (2023). “Digital financial services and human development: current landscape and research prospects”. In: *Information Technology for Development* 29.4, pp. 582–606.

Siano, Alfonso, Lukman Raimi, Maria Palazzo, and Mirela Clementina Panait (2020). “Mobile banking: An innovative solution for increasing financial inclusion in Sub-Saharan African Countries: Evidence from Nigeria”. In: *Sustainability* 12.23, p. 10130.

Suri, Tavneet and William Jack (2016). “The long-run poverty and gender impacts of mobile money”. In: *Science* 354.6317, pp. 1288–1292.

Vickers, Andrew J (2001). “The use of percentage change from baseline as an outcome in a controlled trial is statistically inefficient: a simulation study”. In: *BMC medical research methodology* 1.1, p. 6.

Yakubu, Ibrahim Nandom, Rashad Saani, and Gifty Ewurama Enchill (2025). “Understanding Financial Exclusion in Africa: Challenges and Impacts”. In: *Banking on Inclusion: Overcoming Financial Exclusion in Africa through FinTech Innovations*. Springer, pp. 1–18.