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Effect of Mobile Phone Access on Non-Farming Self-Employment and Income among Female-Headed Households in Tanzania

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Abstract

While having access to mobile phone technologies has shown a promising and relevant effect on rural households' livelihoods, it is important to investigate their effect on other vulnerable groups, such as female-headed households. This paper uses a sample of 1,641 households from Tanzania's national panel data, rounds four and five of 2014/15 and 2020/21, respectively. It employs the 2SRI framework to investigate whether access to mobile phones enhances female-headed households' participation in non-farm self-employment and improves their income. The results indicate that mobile phone technology significantly increased the likelihood of female-headed households participating in non-farm self-employment enterprises by 11.4 percent and improved the share of the income of the self-employment enterprises' share in total household income by 7.9 percent. The estimate further shows evidence that female household heads located in urban areas, skilled and younger experience greater income gains than their counterparts. Thus, the efforts that support and promote mobile phone technology access and usage, coupled with literacy rate improvement among vulnerable sub-populations or groups, are pertinent issues for creating employment and improving income for the groups.

Keywords: mobile phone technology, self-employment, income, female-headed household

JEL Classification: O33; C33; C36; D12; D83.

1. Introduction

In Tanzania, most households' primary employment and source of income is agriculture, particularly the farming sub-sector. According to the National Bureau of Statistics (NBS), the sub-sector employs almost two-thirds (64.2

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percent) of households (NBS, 2021). Farming activities, on the other hand, have been characterised by low earnings due to suboptimal yields. Information asymmetry in inputs and product prices is among the leading constraints for the sector to attain its full potential (Haile et al., 2019; Issahaku et al., 2018; Jensen, 2007). This market inefficiency makes economic agents involved in the sector face higher search and transaction costs (Aker & Mbiti, 2010; Jensen, 2007). The introduction of innovation to minimise such costs could improve the sector's income returns and, consequently, ensure a sustainable higher level of household well-being.

Mobile phone technology innovation has been a useful toolkit to address such market inefficiency. A farm household that has access to a mobile phone has found cheap and quick access to price information regardless of the geographical distance from the market and the presence of poor road networks (Haile et al., 2019; Nakasone & Torero, 2016). Likewise, the reduction of information costs enables farmers to respond quickly to the demand deficit and improve labour market performances (Jensen, 2007). The improvement of product and labour market efficiency has resulted in uplifting both income and non-income benefits to households (Hossain & Samad, 2021; Rajkhowa & Qaim, 2022; Sekabira & Qaim, 2017a). Moreover, such benefits are found to be more prevalent in rural communities, which were the most disadvantageous in terms of information access.

While the mentioned outcomes of mobile phone technologies are relevant for rural pro-poor development, it is also important to understand their effect on other vulnerable sub-populations, such as female-headed households. This group faces disadvantages not only in information access (GSMA, 2021; Hossain & Samad, 2021; Rodríguez-Castelán et al., 2021; Sekabira & Qaim, 2017a) but also in ownership of land (Genicot & Hernandez-de-Benito, 2022; Wineman & Liverpool-Tasie, 2017), which is the primary input for farming activities. This makes their livelihood depend on farming wages, which have small returns and are seasonal-based. Similarly, the limited access to education makes a few of them enrolled in non-farm wage employment to receive a minimum wage, which does not coincide with the rise in the cost of living (World Economic Forum, 2023).

These backdrops reveal that female-headed households have limited access to income opportunities due to a lack of productive assets and competitive advantage in the labour market. An introduction of mobile phone technologies might provide an alternative avenue for self-employment and income opportunities for this vulnerable group. Mobile phone technology might influence female-headed households to participate in non-farm self-employment through access to entrepreneur education, easy access to credit, and a wider social network. Similarly, female-headed households can experience a higher income from non-farm self-employment through higher sales revenue by easily and effectively communicating with customers regardless of geographical distance, accessing transactions using mobile money, and advertising their products using mobile phone internet.

Therefore, the paper examines whether access to mobile phone technology encourages female-headed households to participate in non-farm self-employment and, at the same time, improves income from income generated from these activities. As mentioned, since women are disadvantaged in asset ownership and entry into the labour market, the paper hypothesises that access to such technology by female-headed households will have a positive effect on both participation and income from non-farm self-employment household enterprises.

In this regard, this paper contributes to the literature on the importance of mobile phone technology on household employment and income in several ways. First, most of the recent related works have established an association between mobile phone technology and household income resulting from the use of simple econometric techniques, which cannot address the possible reverse causality between mobile phones and household income. Conversely, this paper employs the two residual inclusive (2SRI) approach developed by Terza et al. (2008) to address three possible potential biases that might arise in such a relationship due to reverse causality, self-selection, or omitted time-invariant variables. Second, while other works have been built using a case study of a small geographical area that might be affected by community settings, the current paper uses a nationally representative sample, which provides more confidence in making generalisations.

Moreover, existing studies have analysed this relationship using the household's total income. This paper provides more policy-relevant evidence by focusing on non-farm household enterprises, as technology can affect different sources of income differently. Similar related works are those of Danquah and Iddrisu (2018), Hossain and Samad (2021), and Rajkhowa and Qaim (2022). However, Danquah and Iddrisu (2018) and Hossain and Samad (2021) use a cross-sectional data set, which makes it difficult to draw credible results, while Rajkhowa and Qaim (2022) do not control for the other sources of income, which is addressed in the current paper. The fourth contribution of the paper is that, in addition to assessing the average effect of mobile phone technology on female-headed household income, this study provides heterogeneous effects for different types of female-headed households based on location, age, and literacy.

The structure of the rest of this paper is as follows: the next section dwells on the literature review – both a theoretical framework and an empirical review of selected prior works. Section 3 discusses the methodology, while section 4 presents and discusses the empirical results. The final section, section 5, gives the study's conclusion and policy implications.

2. Theoretical and Empirical Perspectives

2.1 Theoretical Framework

This study is built on the premises of consumer theory. One of the foremost assumptions of this theory is that consumers are rational when facing a choice problem. The consumer's preferences enable a clear understanding of these choices (Varian, 2014). Consumer preferences over alternative bundles are used to explain the consumer's goals in the classic consumer model. The behavioural goal is to maximise these preferences while adhering to a resource constraint that limits trading options. The simplest way to describe these preferences is to use the utility maximisation model. The utility maximisation model hypothesises that consumers allocate their resources to commodities that yield optimal satisfaction.

However, consumer utility cannot be observed; instead, the outcomes of the choices can be observed. Thus, a utility that is determined by a set of exogenous variables influences the choice outcome. In this study, what can be observed is whether households access or do not access mobile phone technology. Henceforth, the decision to use this technology or not depends on whether the utility derived from using it is greater than that of not using it. One of the key assumptions in this model is that a female-headed household faces only two choices: use or not use mobile technology. This work will extend the existing theory by exploring how these behavioural choices on mobile phone technology influence the likelihood of households participating in non-farm self-employment activities and, at the same time, whether such participation increases household income from income generated from self-employment activities.

2.2 Empirical Literature

Since the start of the twenty-first century, innovation has become a primary driver of development (UNCTAD, 2021). Among recent noble innovations is that in the Information and Communication Technologies (ICTs) sector, such as the use of mobile phones. The existing body of literature has consistently indicated that access to mobile phone technology is important to realise income growth, particularly for the marginalised and vulnerable rural population.

Hübler and Hartje (2016), Ma et al. (2018), Hossain and Samad (2021), and Khan et al. (2022) have used a cross-sectional rural household data set to analyse the effect of mobile phone technology on household income. Hübler and Hartje (2016) use surveyed data from rural Southeast Asia and a linear endogenous treatment regression framework and find that access to smartphones has a positive effect on household total income as measured by the log of annual per capita. This result is concurrent with the work of Ma et al. (2018). In their study of rural households in China and the use of the control function approach, they find that household heads that participate in off-farming work and use smartphones realize a higher income measured by annual per capita compared to the full-time farming household and smartphone-free households.

In the same vein, the recent works of Hossain and Samad (2021) and Khan et al. (2022) extend the analysis by examining the effect of the technology beyond household total income. Hossain and Samad (2021) analyse data from off-grid rural areas in Bangladesh and use propensity score-based weighted regressions to assess the influence of mobile phone access on household income derived from both agricultural and non-agricultural sources. They conclude that access to a mobile phone increases the likelihood of a household improving their income from both agriculture and non-agriculture activities. Similar results were obtained from the work of Khan et al. (2022) using data from rural wheat growers in four districts in the Khyber Pakhtunkhwa Province of Pakistan and a propensity score matching approach.

On the other hand, other researchers use rural household panel data to improve the reliability of the results (Kikulwe et al., 2014; Rajkhowa & Qaim, 2022; Sekabira & Qaim, 2017a, 2017b). Kikulwe et al. (2014) use data from smallholder banana growers in central and eastern Kenya to understand how mobile phone technology impacts household total income and farm income. They find the use mobile money as an innovation of mobile phone technology by farm households had a positive effect on household total income and farm income. A similar conclusion was achieved by Sekabira and Qaim (2017a) using data from smallholder coffee growers in central Uganda and similar econometric techniques, random effect and fixed effect models.

Likewise, studies by Rajkhowa and Qaim (2022) and Sekabira and Qaim (2017b) provide additional evidence of the impact of mobile phone technology on household off-farming income, despite not controlling for other sources of household income. Sekabira and Qaim (2017b) use a mobile phone technology innovation, mobile money, and the data of smallholder coffee growers in central Uganda, showing that this technology has a positive effect on household off-farm income. Parallel results were obtained by Rajkhowa and Qaim (2022) using data from rural households in India that participate in off-farm activities. They find that access to mobile phones and participation in off-farming activities of households had a positive and significant effect on household income.

While the aforementioned studies have shown evidence of mobile phone technologies positively impacting rural households' development, it is also important to explore their impact on another vulnerable sub-population, female-headed households. Understanding how access to mobile phone technology affects female-headed households, particularly in sub-Saharan Africa, is relevant since women are disadvantaged in accessing and owning productive assets such as land and mobile phones (Genicot & Hernandez-de-Benito, 2022; GSMA, 2021; Rodríguez-Castelán et al., 2021; Wineman & Liverpool-Tasie, 2017). Specifically, community norms in these regions make this group disadvantaged in land ownership, which is one of the primary inputs for main income source activities such as farming and livestock keeping. Similarly, limited access to education causes a minority of women who engage in wage employment end up earning a minimum wage that is not commensurate with the rising cost of living (World Economic Forum, 2023).

Thus, this paper contributes to the existing literature by analysing the impact of mobile phone technology on female-headed households' participation in non-farm self-employment activities and how such participation contributes to their income. The study uses the Tanzanian National Panel data set, the fourth and fifth rounds of 2014/15 and 2020/21, and employs the 2SRI methodological framework to address three possible potential biases from mobile phone access and outcomes variables of interest, namely reverse causality, self-selection, and omitted time-invariant variables. A similar work that uses the national representation on non-farm households data set is that by Danquah and Iddrisu (2018). However, it relies on the cross-section data set, which makes it difficult to draw a causal effect. In addition, unlike other works, this paper controls for the other income sources that a household engages in, as technology can have varying effects on them. Furthermore, this paper estimates the heterogeneous effect of female-headed households based on location, age, and literacy.

3. Methodology

3.1 Analytical Framework

The main interest of this study is to examine the effect of access to mobile phones on non-farm self-employment and the income of female-headed households. However, the main explanatory variable, household access to mobile phones is likely to be endogenous in the model. Both observed and unobserved factors can influence the household's decision to own a mobile phone. Wealthier households are more likely to have a mobile phone because they have a higher income. This reverse causality might bias the outcome variable by understating or overstating the true effect of the treatment. In terms of the unobservable factors, a higher income generated from non-farm self-employment enterprises of the households might be attributed to the personal business innate ability, self-motivation, or creativity, which might bias the result by being correlated with the error term. The third possible cause of endogeneity is self-selection of households that own mobile phones. The service providers of mobile phones are distributed non-randomly to households that participate in non-farm self-employment activities, which might also influence the outcome variable.

To address these potential biases, a study employs the two-stage residual inclusive (2SRI) method, which is capable of addressing the potential endogeneity bias between mobile phone access and non-farm self-employment and income (Terza et al., 2008; Tesfaye & Tirivayi, 2020; Wooldridge, 2014). The first stage of the method requires at least one instrument that explains the variation of the mobile phone but does not affect the outcome variable. This work uses technology diffusion at the community level, similar to the related prior works (Aker & Mbiti, 2010; Bukari & Koomson, 2020). Technology diffusion is measured by the proportion of the population using a mobile phone at the community level, excluding the household under consideration. The paper assumes that peer mobile phone adoption and use will positively influence neighbourhood household ownership and use of mobile phone technologies. However, it is not expected to affect the outcomes of interest, household participation in non-farm self-employment enterprises, or household income.

The econometric model in the first stage of analysis is the decision equation of the female-headed households over the ownership of a mobile phone. The structural form equation follows the related works of Twumasi et al. (2021) and Matsuura et al. (2023), and is expressed as:

$$Mp_{ht} = \alpha X_{ht} + \beta Z_{ht} + \gamma \bar{M}_{ht} + \rho T_t + \varepsilon_{ht} \qquad (1)$$

Where Mp_{ht} indicates the status of the household h in the year t whether accessing a mobile phone or not, such that it equals to 1 when accessed and zero otherwise. X_{ht} is a vector of controls that might influence female-headed household decisions to access a mobile phone, Z_{ht} is the instrument variable, and $\bar{M}_{ht}$ is the average of the all-time varying variables in the model. T_t is a time fixed effect and ε_{ht} is a time-varying error.

We estimate equation (1) by using the correlated random effect (CRE) probit, also known as the pool maximum likelihood estimator (Pool MLE). The advantage of this approach over the classical measures of the fixed effect (FE) estimator and random effect (RE) estimator is that it relaxes a strict assumption of RE that unobserved time-invariant variables are exogenous to the explanatory variables in the model and avoids incidental parameter problems associated with the FE estimator (Chamberlain, 1982; Mundlak, 1978). Moreover, the inclusion of an average of the all-time-varying variables in the model enables the control of time-invariant unobservable factors (Wooldridge, 2019).

In the second stage of the estimation, the residual obtained in the first stage of the estimation is included in the outcome equation to take account of unobservable heterogeneity. The functional form of the estimation equation also maintains the endogeneity of mobile phone access and other exogenous explanatory variables defined above. It is expressed as:

$$Y_{ht} = \varphi Mp_{ht} + \phi \widehat{Mp}_{ht} + \psi X_{ht} + \eta \bar{A}_{ht} + \sigma T_t + \mu_{ht} \qquad (2)$$

Where Y_{ht} indicates outcome variables of household h in the year t, Mp_{ht} is the mobile phone status of household h in year t, $\widehat{Mp}_{ht}$ is the residuals obtained from the estimation of equation (1), and $\bar{A}_{ht}$ is the mean value of all time-varying variables in the model. X_{ht}, T_t and μ_{ht} are the same as defined in equation (1).

From equation (2), the parameter of interest is φ. In the first outcome variable, which is non-farm self-employment status, the paper hypothesizes that when φ is positive and statistically significant, then access to a mobile phone by the female-headed household will increase the likelihood of the household participating in non-farm self-employment activities; otherwise, it is true. Since the outcome variable is binary, the study employs a correlated random effect (CRE) probit model to estimate the effect of access to mobile phones on female-headed household participation in non-farm self-employment activities, similar to the first-stage estimation. We also use the fixed effect (FE) logit model as the robustness check on the primary estimation, where mobile phone access is treated as exogenous.

On the other hand, in the second specification, when the outcome variable is non-farm self-employment income, when φ is positive and statistically significant, then access to a mobile phone increases non-farm self-employment household income to total income by a ratio of φ. To estimate such a relationship, we use a correlated random effect (CRE) estimator as an alternative to the FE estimator (Mundlak, 1978) to take advantage of the CRE as explained above. As a robustness check, we also estimate using a pool OLS, where access to a mobile phone is assumed to be exogenous.

3.2 Data Sources and Measurement of Variables

This study uses nationally collected household longitudinal survey data on living standards in Tanzania and is focused on the latest two waves: the fourth wave of 2014/15 and the fifth wave of 2020/21. The choice of these two waves was made based on the introduction of a new refresh sample in the fourth round. This measure of introducing a new sample was implemented to reduce attrition bias caused by households leaving the survey over time and improve the reliability of the sample due to changes in administration boundaries and demographic shifts. On the other hand, the fifth round tracks the entire refresh sample of the fourth wave (NBS, 2022). These surveys are part of the Living Standard Measurement Study-Integrated Survey on Agriculture (LSMS-ISA) conducted by the Tanzania National Bureau of Statistics (NBS) with the assistance of the World Bank.

The National panel Survey (NPS) continues to maintain a low attrition rate (9.1 percent) to minimize the sample bias that might be caused by the non-random drop of respondents. Out of the 3,352 households interviewed in the original refresh sample of 2014/15, a total of 3,052 households were successfully interviewed in 2020/21. In this study, the sample is limited to female-headed household in order to answer the research question raised. This results in a sample size of 1,641 households for study analysis.

In each round, the surveys contain detailed information related to the household sources of income and whether the household has a mobile phone. The information on income sources was extracted from the household questionnaire, agriculture questionnaire, and livestock questionnaire based on the economic activities in which households participate. Such broad and detailed information provides an opportunity to explore the contribution of each source of income to a household's its total income. The data set also contains information related to household status in terms of mobile phone ownership and participation in non-farm self-employment activities, which is useful for the study analysis.

3.2.1 Variables Selection and Measurement

The outcome variables for this paper are household non-farm self-employment status and non-farm self-employment income. A household's non-farm self-employment status is a dichotomous variable that indicates 1 if the household participates in non-farm self-employment activities and zero otherwise. On the other hand, the income share of non-farm self-employment to the total household income is an indicator used for non-farm self-employment income. This is measured by the share of the income generated from non-farm self-employment activities in the total household income. The choice of the income share rather than log values of income is because the interest of the study is to compute the contribution of the non-farm self-employment income to the total income impacted by the use of mobile phone technology. Moreover, the use of shares does not overweight the household with a higher income and is less prone to the higher income fluctuating over time (Broeck et al., 2020). Non-farm self-employment income is calculated from the net profit a household obtains from the household's enterprises, such as a shop or trade business that does not depend on the agriculture season.

The household total income is computed from a wide range of economic activities in which households participate to generate income. This includes agriculture and non-agriculture wage employment, off-farm self-employment, livestock keeping, and other sources. Specifically, agriculture wage employment income is income generated from being employed in on-farm activities such as land preparation, planting, weeding, and harvesting. Non-agriculture wage is income generated from being employed in government, private sector, non-governmental organizations, in the form of salary and other work benefits.

Table 1: Variables Description and Expected Sign of the Explanatory Variables Used

Variables	Description	Expected Sign	
		NFSE	IS
Outcome variables			
Income share (IS)	The proportion of the income generated from non-farm self-employment activities to the total household income.		
Non-farm self-employment (NFSE)	A dummy variable that indicates 1 if the household head participates in non-farm self-employment activities, and zero otherwise.		
Main explanatory variable			
Mobile phone ownership	A dummy variable that indicates 1 if the female-headed household owns a mobile phone and zero otherwise.	+	+
Control variables			
Household head education	Numbers of years a household head spends on schooling.	+	+
Age of household head	Number of years of household head.	-	-
Household uses bank account	A dummy variable indicates 1 if the household owns a bank account and zero otherwise.	+	+
SACCOS member	A dummy variable indicates 1 if the household is a member of Savings and Credit Cooperative Organisations and zero otherwise.	+	+
Household size	Number of family members in a household.	+/-	-
Labour force participation	The proportion of adult members in households who are in the labour force.	+	+
Electricity access	A dummy variable indicates 1 if the household accesses electricity from the national grid and zero otherwise.	+	+
Dwelling ownership	A dummy variable shows 1 if the respondent household owns the main residence and zero otherwise.	+	+
Household assets	An index for household durable assets	+	+
Rural household	A dichotomous variable indicates 1 for rural households and zero for urban households.	-	-

Regarding the income generated from off-farm self-employment activities, it involves the profit generated for the household engaged in the agriculture by-product trade and fish trade activities[1]. The livestock income is computed from the profit generated from livestock products such as milk, eggs, skin, and live animals. Other sources of income involve income generated from property rent, pension, interest, asset sales, lottery, inheritance, remittance or financial assistance, and in-kind support such as scholarships, and the value of food aid.

The main explanatory variable of interest is access to mobile phone technology, which a dummy variable; indicating 1 if the female-headed household owns a mobile phone and zero otherwise. Other explanatory variables used in this paper are derived from relevant related prior research by Danquah and Iddrisu (2018), Leng et al. (2020), and Rajkhowa and Qaim (2022). These include household characteristics such as household size, household labour force, household asset index[2], access to electricity, and dwelling ownership. Individual characteristics include the household head's education, years of schooling, and status of use of financial services. The description of the variables used and expected sign of the explanatory variables used in this paper is presented in Table 1.

4. Results and Discussion

We provide the findings and discussion of the results; we first show the descriptive statistics of the variables used in the analysis, followed by a detailed explanation of the empirical results. The empirical results first indicate the effect of access to mobile phones on non-farm self-employment participation for female-headed households. Second, the discussion on how access to a mobile phone affects the share of a household's total income from the income generated from non-farm self-employment activities is presented, followed by the heterogeneity effect of access to a mobile phone on a female-headed household's income.

[1] The study does not include the income generated from fish trade in the fifth round, 2020/21, because no data was collected from the fisheries sector.

[2] The household asset index is computed using principal component analysis (PCA), as it is widely used in empirical studies (Choumert-Nkolo et al., 2019; Mckenzie, 2004; Rahut et al., 2018, 2019). This work is calculated using reported household durable assets, excluding telecommunication items such as mobile phones, televisions, radios, and the like.

4.1 Descriptive Analysis

Table 2 indicates the summary statistics for the variables used in this paper. The average share of income that comes from non-farm self-employment to the household's total income is 32.1 percent. This shows the importance of non-farm self-employment for female-headed households' livelihoods, as one-third of their incomes come from this sub-sector. The data set also shows that the number of female-headed households participating in this economic activity is relatively large, at 45.1 percent of the sampled population. Moreover, the results indicate that mobile phones are are also widely adopted by female-headed households (74.9 percent of the sample). In the first round of the data set, only 27.6 percent of households did not own a mobile phone, which fell by six percent in the second wave.

In terms of socioeconomic characteristics of households, Table 2 further shows that the average size of the household member is four persons, with 31.9 percent and 67.3 percent of survey households accessing electricity and owning a dwelling, respectively. On average, 86.4 percent of household members participate in the labour force, 57.5 percent of the reported households reside in rural areas, and household assets are indicated by an index generated by using principal component analysis. The negative sign on the score shows that the majority of the sample households have limited ownership of durable household assets. This indicates that a large proportion of the sample population has a lower socioeconomic status, and this might be attributed to the limited income-generation activities. Hence, access to mobile phone technology might open new avenues for income sources.

The results further show that the average year of education for female-headed households is 4.9, and their mean age is 49.7 years. The sampled population shows a low rate of female-headed households using bank services (15.9 percent) and participating in saving and credit cooperative organisations (5.6 percent).

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Table 2: Summary Statistics of the Estimation Variables

Variables	(1) NPS Wave 4 2014/15	(2) NPS Wave 5 2020/21	(3) Pooled NPS Wave 4&5
Outcome variables			
Income share	0.303	0.348	0.321
	(0.409)	(0.430)	(0.418)
Non-farm self-employment (dummy)	0.467	0.429	0.451
	(0.499)	(0.495)	(0.498)
Main explanatory variable			
Mobile phone ownership (dummy)	0.724	0.784	0.749
	(0.447)	(0.412)	(0.434)
Control variables			
Household head education (years)	4.676	5.066	4.839
	(4.117)	(4.279)	(4.188)
Age of household head (years)	47.23	53.52	49.86
	(15.73)	(14.96)	(15.72)
Household uses bank account (dummy)	0.157	0.138	0.149
	(0.364)	(0.346)	(0.356)
SACCOS member (dummy)	0.0607	0.0510	0.0567
	(0.239)	(0.220)	(0.231)
Household size	4.001	4.124	4.052
	(2.618)	(2.686)	(2.647)
Labor force participation	0.879	0.843	0.864
	(0.233)	(0.257)	(0.244)
Electricity access (dummy)	0.267	0.392	0.319
	(0.443)	(0.489)	(0.466)
Dwelling ownership (dummy)	0.645	0.713	0.673
	(0.479)	(0.453)	(0.469)
Household assets (index)	-0.680	-0.717	-0.696
	(1.919)	(1.712)	(1.835)
Rural household (dummy)	0.565	0.589	0.575
	(0.496)	(0.492)	(0.494)
Observations	1641		

Note: Mean value reported and standard deviation in parentheses

4.2 Effect of Mobile Phone on Non-Farm Self-Employment

We present the results of the effect of access to mobile phones on female-headed households to participate in non-farm self-employment enterprise activities. Table 3 reports the findings using CRE probit and FE logit of the female-headed household sample on the likelihood of participating in non-farm self-employment enterprise activities. Column (1) indicates the main results using CRE probit, and column (2) is for robustness checks using the FE logit model.

Table 3: The Effect of Mobile Phone Technologies on Household Participation in Non-Farm Self-Employment Enterprise Activities

Variable	(1)	(2)
	CRE probit	FE logit
Mobile phone ownership (dummy)	0.114***	0.930***
	(0.032)	(0.227)
Household head education (years)	-0.009	-0.042
	(0.016)	(0.028)
Age of household head (years)	-0.016***	-0.017**
	(0.005)	(0.007)
Household uses bank account (dummy)	-0.047	-0.909***
	(0.067)	(0.285)
SACCOS member (dummy)	-0.025	1.109***
	(0.076)	(0.375)
Household size	-0.010	0.096***
	(0.016)	(0.036)
Labour force participation	0.095	1.021***
	(0.076)	(0.375)
Electricity access (dummy)	-0.102	-0.000
	(0.063)	(0.248)
Dwelling ownership (dummy)	-0.039	-0.018
	(0.056)	(0.212)
Household assets (index)	0.059***	0.375***
	(0.021)	(0.084)
Rural household (dummy)	-0.032	-0.910***
	(0.146)	(0.252)
Region	No	Yes
Year	No	Yes
Observations	1617	1617

Note: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The result from the interest variable is tenable. The marginal effect of a female-headed household owning a mobile phone increases the likelihood of participating in the non-farm self-employment enterprise by 11.4 percent and is statistically significant at the conventional level. The second model specification in column (2), fixed effect logit, also shows a positive and statistically significant effect of access to mobile phone technology on female-headed household participation in non-farm self-employment activities; however, the presence of bias overstates the true effect. These results are similar to the recent study of Rajkhowa and Qaim (2022) in rural Indian households using a fixed-effect linear probability model. They find that access to mobile phone technology improves the probability of households participating in off-farm employment activities by 4 percent.

The other control variables that show a positive effect of female-headed households participating in non-farm self-employment enterprises are household labour force participation and household assets. An additional household asset increases the likelihood of the female-headed household participating in non-farm self-employment enterprises by 6 percent and is statistically significant at the conventional level in the main model. This finding implies that initial capital and assets play a substantial role in household participation in self-employment activities, as documented in the related empirical works of Nagler and Naudé (2017) and Broeck and Kilic (2019). In terms of household labour force participation, though it has a positive effect, it is statistically insignificant. In all model specifications, the younger female-headed household shows a 2 percent higher likelihood of participating in non-farm self-employment enterprises compared to the older female-headed household. This finding substantiates the assertion that individual ageing tends to be conservative with technological advancement (Khan et al., 2022; Ma et al., 2018; Rahayu & Riyanto, 2020). The remaining covariates in the main model have a negative and insignificant effect on the female-headed households participating in non-farm self-employment enterprises. This result suggests that access to mobile phone technology could even induce households with disadvantages in accessing physical infrastructure such as electricity and bank services into non-farm self-employment enterprises.

4.3 Effect of Mobile Phone on Non-Farm Household Income

The second evidence presented in this study demonstrates the effect of mobile phone technologies on household self-employment income share to total household income. Table 4 displays the results using the correlated random effect (CRE) model and Pool OLS. Column (1) contains the result of the main estimation model, CRE, and column (2) is for the robustness check using Pool OLS.

Table 4: The Effect of Mobile Phone Technologies on Non-Farm Household Income

Variables	(1)	(2)
	CRE	Pool OLS
Mobile phone ownership (dummy)	0.079**	0.103***
	(0.031)	(0.030)
Household head education (years)	-0.015	-0.015
	(0.016)	(0.016)
Age of household head (years)	-0.008*	-0.009**
	(0.004)	(0.005)
Household uses bank account (dummy)	-0.140*	-0.125*
	(0.073)	(0.073)
SACCOS member (dummy)	-0.090	-0.085
	(0.082)	(0.083)
Household size	-0.012	0.000
	(0.014)	(0.014)
Labour force participation	0.014	0.026
	(0.076)	(0.079)
Electricity access (dummy)	-0.107	-0.125*
	(0.067)	(0.067)
Dwelling ownership (dummy)	-0.034	-0.017
	(0.052)	(0.052)
Household assets (index)	0.043**	0.046**
	(0.022)	(0.022)
Rural household (dummy)	-0.051	-0.007
	(0.124)	(0.126)
Mundlak Variables	Yes	Yes
Region	Yes	Yes
Year	Yes	Yes
Observations	1420	1420

Note: Standard errors in parentheses are clustered at the household level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The result from the main estimation model shows that access to mobile phone technology increases the share of a non-farm self-employed household's enterprise income in total household income by 7.9 percent. In column (2), where mobile phone technology access is treated as exogenous, it is also indicates that mobile phone technology increases the ratio of non-farming self-employment enterprises' income to total household income. However, the second model specification overstates the effect of mobile phone technology on income generated from self-employment activities due to biases. The possible mechanisms of mobile phone technology for increasing household income from income generated from non-farm self-employment activities might result from the improvement of household enterprise sales revenue. Mobile phone technology improves the profit margin of household enterprises by reducing business transaction costs through communication and easy follow-up of customers, receiving payments using mobile money, and reducing advertisement costs using mobile phone internet applications, irrespective of the geographical distance to the customers.

This finding is similar to the related works of Danquah and Iddrisu (2018) and Rajkhowa and Qaim (2022). Danquah and Iddrisu (2018) show that access to mobile phone technology improves the sales revenue of non-farm household enterprises by 41.5 percent using national representative cross-section data in Ghana and the OLS framework. Likewise, Rajkhowa and Qaim (2022) indicate that access to mobile phone technology increases the total household income expressed in logarithmic form by 11 percent using rural India household data and a fixed effect model.

Other explanatory variables that have shown a significant effect on household income in the main model are the age of the household head, household use of the bank account, and household assets. The younger household heads have a higher effect on household income than the older household heads, and is statistically at the conventional level, similar to the results obtained by Ma et al. (2018). This finding might be attributed to the fact that youth are more innovative and creative in technology application (Khan et al., 2022; Rahayu & Riyanto, 2020).

The use of bank accounts has been shown to shrink the share of non-farm household enterprises to the household's total income. This is in line with the study by Rajkhowa and Qaim (2022), which reported that access to credit in formal financial institutions has a negative impact on household total income. This result could be explained by the higher transaction costs associated with traditional formal financial institutions (Kikulwe et al., 2014; Munyegera & Matsumoto, 2016). A further result shows that household assets have a positive effect on the share of the income of non-farming self-employment enterprises to the total income, as documented in the related works of Broeck and Kilic (2019) and Rajkhowa and Qaim (2022). The results suggest the reliance of household wealth on running non-farm household enterprises, as the majority of the sampled population is excluded from formal financial institutions, as indicated in Table 2.

4.4 Heterogeneous Effect of Mobile Phone Technology on Household Income

We provide further estimate of results beyond the utilised sample average effect. Table 5 displays the heterogeneous effect of female-headed households' access to mobile phone technology based on location, age, and literacy using the CRE framework. The estimated results show that a younger, female-headed household benefits more than an older, female-headed household. The fact that the older age groups are relatively sceptical to new technology may be linked to the limited benefits derived from technology applications. The positive and statistically significant effect is in line with those reported in other studies (Khan et al., 2022; Ma et al., 2018; Rahayu & Riyanto, 2020; Sekabira & Qaim, 2017b).

Table 5: The Heterogeneous Effect of Mobile Phone Technology on Non-Farm Household Income

Variables	Age of Head<45		Location Type		Literacy Head	
	No	Yes	Rural	Urban	No	Yes
Mobile phone ownership (dummy)	0.006	0.084*	0.046	0.150**	0.068	0.121**
	(0.041)	(0.048)	(0.035)	(0.069)	(0.043)	(0.049)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak Variables	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	707	713	767	653	516	868

Note: Standard errors in parentheses are clustered at the household level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Similarly, urban female-headed households are found to derive more benefit from access to mobile phone technology on their self-employment income than their counterparts, the rural households. This result might be attributed to the fact that in urban areas, non-agricultural activities are the primary economic activity, and women with disadvantages on the labour market rely primarily on self-employment enterprises for their livelihoods. These results differ from Danquah and Iddrisu (2018) when using aggregate cross-section household data.

Furthermore, the results from the status of female-headed literacy indicate the importance of quality education in reaping the benefit of technology. A female-headed household that is capable of reading and writing benefits more compare to an illiterate female-headed household. This result implies that while investing in technology is necessary to realise income growth, investing in quality education is paramount to attaining such sustainable growth. This result is related to the work of Bahia et al. (2021). Bahia et al. (2021) demonstrate that literate women who are exposed to 3G broadband coverage benefit from transitioning from self-employment farms to non-farm self-employment activities using panel data and the different-in-differences methodology.

5. Conclusion and Policy Implications

Previous studies widely document the importance of mobile phone technology for household livelihoods using the rural household data set. Rural households have faced many challenges in accessing economic opportunities and improving their income. One of the main drivers of these challenges is the high level of information asymmetry among economic agents. This market inefficiency in both labour and goods markets leads to unnecessary higher transaction and searching costs. The introduction of mobile phone technology provides an important innovation to address such a challenge by reducing friction in the goods market, which in turn improves demand in the labour and goods markets.

This work contributes to these studies beyond rural settings by investigating whether such technological innovation contributes to the other disadvantaged sub-population, the female-headed households. This sub-population is disadvantaged in terms of information access, productive resource ownership, and competitive edge in the labour market. The paper investigated this by testing two related hypotheses. Firstly, the paper examined whether access to mobile phone technology increases the probability of female-headed households participating in non-farm self-employment enterprises and, second, whether it improved household income from income generated from non-farm self-employment enterprise activities.

The paper tested these hypotheses using the fourth and fifth round of the Tanzania panel data of 2014/15 and 2020/21 and employed the 2SRI approach framework to address the possible bias from such a relationship. The findings of the estimates show that a mobile phone increases the likelihood of the female-headed household to participate in non-farm self-employment enterprises by 11.4 percent and also improves the share of the self-employment enterprise's income in total household income by 7.9 percent at the conventional level of significance. Further, the study revealed a heterogeneous effect of mobile phone technology on the female-headed household sub-population.Younger female-headed households, located in urban areas, and who are skilled, have higher income benefits than their counterparts.

These findings have important policy implications; continuing to invest and promote technology uptake and usage among marginalised sub-populations is important in attaining inclusive development through job creation and income improvements. Moreover, policies for improving the quality of education are paramount in the current fourth industrial revolution and in order to catch up with technological change and innovation.

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